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Transparency in Decision-Making: The Role of Explainable AI (XAI) in Customer Churn Analysis

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ABSTRACT In many industries, such as the telecommunications industry, identifying the causes of customer churn is a primary challenge. In the telecommunications industry, it is of great importance to predict which customers will abandon or continue their subscriptions. Machine learning and data science offer numerous solutions to this problem. These proposed solutions have an important place in decision-making processes in various sectors. This study aims to predict lost customers using machine learning algorithms and explain the reasons behind them. Linear Regression, Logistic Regression, Naive Bayes, Decision Tree, Random Forest, K-Nearest Neighbors (KNN), Gradient Boosting, XGBoost (eXtreme Gradient Boosting), LightGBM, AdaBoost, and CatBoost were used to find the classification with the best performance on the dataset used. In this process, performance metrics such as Accuracy, Precision, Recall, and F1-Score are used to compare the performance of models. Finally, the LightGBM model, which gave the highest accuracy value (73.085%), was explained using explainable artificial intelligence (XAI) algorithms.

KEYWORDS
Customer churn prediction
eXplainable artificial intelligence (XAI)
LIME
SHAP

INTRODUCTION

The literature on telecommunications customer churn behavior has grown in importance and volume since the early 2000s. This study performed a quantitative bibliometric retrospection of selected journals that qualified for the ABDC journal quality list to examine relevant studies published by them on customer churn research in telecommunication. Using bibliometric data from 175 research articles available in the Scopus database, this review sheds light on the publication trends, articles, stakeholders, prevalent research techniques, and topics of interest over three decades (1985–2019). According to the findings of this review, the current level of contributions are manifested through ten overarching groups of scholarship-namely churn prediction and modeling, feature selection techniques and comparison, customer retention strategy and relationship management, service recovery, pricing and switching cost, legislation, legal, and policy, word-of-mouth and post-switching behavior, new service adoption, brand credibility, and loyalty. The existing literature has predominantly utilized quantitative methods to their full potential. For far too long, scholars, according to the study's central thesis, have ignored the metatheoretical consequences of relying solely on a logical positivism paradigm. In addition, we highlight research directions and the need for customer churn research to go beyond feature selection and modeling (Bhattacharyya and Dash 2022; Ribeiro *et al.* 2024).

Against this backdrop, an ambitious research endeavor unfolds within the telecommunications domain, embracing methodologies encompassing customer churn analysis, Churn Analysis, and Data Mining. This study's primary aim is to decipher the underpinnings of customer attrition within telecom companies and unravel the distinctive profiles of lost customers. Embarking on a meticulous exploration, this study scrutinizes customer churn in the telecommunications sector through a rigorous analysis of 50,137 customers utilizing advanced machine learning techniques. The dataset employed for predicting customer churn is rich in complexity, comprising 55 customer-related parameters. This analytical undertaking emerges as a pivotal stride toward comprehending and forestalling customer attrition within the industry. Subsequent sections of this article will unfold a comprehensive literature review, delving into the realms of customer churn, machine learning, and the telecommunications industry. A detailed exposition of the proposed methodology and algorithms will follow, with section 4 housing information on the application and analysis results. The article will culminate with a results and discussion section.

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In recent years, the utilization of Artificial Intelligence (AI) has proliferated across various domains, offering innovative solutions to complex problems. However, the opaque nature of many AI models poses significant challenges in understanding and trusting their outcomes, leading to concerns about their reliability and accountability. This has spurred a growing interest in eXplainable AI (XAI) methods, which aim to enhance transparency and interpretability in AI systems by providing insights into the decision-making processes of these models. As a result, the adoption of XAI techniques has been on the rise, reflecting a broader recognition of the importance of explainability in AI applications. The significance of explainability in meeting legal demands, addressing user concerns, and aligning with application requirements underscores the importance of XAI in ensuring the reliability and accountability of AI systems. This highlights the relevance of tailoring explanation content to specific user types and application contexts (Ali *et al.* 2023). By presenting an overview of the current state of taxonomies in XAI research and proposing strategies for improvement, this paper aims to provide scholars with valuable insights into the evolving landscape of XAI and facilitate informed decision-making in method selection and application (Speith 2022). This systematic review contributes to the growing body of knowledge on XAI by organizing and clustering scientific studies based on a hierarchical system. By analyzing existing taxonomies and peer-reviewed literature, the review identifies key theories and notions related to explainability, as well as evaluation approaches for assessing the effectiveness of XAI methods (Vilone and Longo 2021).

This escalating challenge underscores the exigency for corporations to pioneer innovative analysis methodologies, thereby discerning the causes of customer churn and augmenting customer allegiance. In this pursuit, the emerging field of Explainable Artificial Intelligence (XAI) plays a crucial role.XAI aims to make the decision processes of machine learning models, such as those used in customer churn analysis, more understandable and transparent. Two prominent techniques in XAI, namely Local Interpretable Model-agnostic Explanations (LIME) and SHapley Additive exPlanations (SHAP), offer valuable insights into the inner workings of complex models.LIME, a model-agnostic method, achieves interpretability by simplifying the understanding of a specific prediction. It perturbs the input data, observes the changes in the model's predictions, and builds a local, interpretable model to explain the decision-making process effectively. On the other hand, SHAP, grounded in Shapley values from game theory, quantifies the contribution of each feature to a model's prediction. By assigning values to each feature, SHAP provides a nuanced understanding of how individual features impact the model's decisions.

In the telecommunications domain, the integration of XAI methodologies, including LIME and SHAP, becomes instrumental. These techniques enable a deeper comprehension of the factors influencing customer churn predictions. The subsequent sections of this article will delve into the comprehensive literature review, incorporating discussions on customer churn, machine learning, and the telecommunications industry. Additionally, a detailed exposition of the proposed methodology, including the application of XAI techniques, will follow, culminating in the analysis results and discussions. In the competitive milieu of today, the burgeoning significance of the customer relationship management (CRM) process is underscored by a paradigm that situates the customer at the epicenter of the customer economy. Essential facets of an effective CRM process, namely customer acquisition, retention, loss, and recovery, accentuate the integral role this study is poised to play. The anticipation is that this research will not only contribute significantly to the comprehension of customer churn in the telecommunications industry but will also offer insights crucial for prevention strategies.

RELATED WORKS

In the field of customer churn prediction in the telecommunications industry, various studies have contributed to understanding and addressing this critical issue. Pettersson (2004) emphasized the effectiveness of Statistical Process Control (SPC) methods in tracking customer movements and churn. These methods, as discussed by Pettersson, involve monitoring usage patterns to detect decreasing volumes indicative of churn.

Feature selection is a crucial aspect of customer churn prediction models. Huang *et al.* (2010) proposed a new filter feature selection approach specifically tailored for telecommunications churn prediction. This underscores the need for advanced techniques in a competitive market where efficient churn prediction models are essential for retaining customers. Imbalance in data distribution is a common challenge in churn prediction. Idris *et al.* (2012) explored the significance of Particle Swarm Optimization (PSO)-based undersampling in collaboration with various feature reduction techniques. Their study addressed the imbalanced data distribution problem, contributing to the development of more robust churn prediction models.

Non-technical innovation, such as customer engagement strategies, has been examined by Cambra-Fierro *et al.* (2013) in the context of marketing capabilities and commercial processes. This perspective highlights the importance of innovative approaches beyond technical aspects in retaining customers. Shen *et al.* (2014) focused on improving churn prediction by employing a complementary fusion of multilayer features based on factorization and construction. Their work delves into the optimization of feature subsets and prediction techniques for enhanced accuracy in the telecommunications industry.

Alawin and Al-ma'aitah (2014) contributed to decision-making in the telecom sector by proposing research models and utilizing On-Line Analytic Processing (OLAP) and On-Line Data Mining (OLDM) techniques. Their models aimed at optimizing sales points, reducing costs, and identifying profitable customers. Chouiekh and Haj (2017) addressed the importance of machine learning techniques, specifically in the prepaid subscriber segment of the telecom industry in Morocco. Their study aimed at determining the best prediction model to enhance the competitiveness of the Moroccan telecommunications sector. Yuan (2023) investigated telecom customer churn prediction using a composite model composed of logistic regression and neural networks. The adoption of a combinatorial model highlights the need for sophisticated approaches in predicting customer churn.

In addition to telecom-related studies, Gaurav and Tiwari (2023)) explored the application of Explainable AI (XAI) in the banking sector, specifically addressing inefficiencies in the onboarding process. This reflects a broader perspective on the use of advanced technologies across different industries. The acceptance of telemedicine technology among health professionals was studied by Mohammed *et al.* (2023) in the context of the Moroccan public sector. Their research contributes to understanding the factors influencing the successful implementation of telemedicine technology. Franchini and Balzan (2023) introduced an influential theory of increasing returns to explain lock-in phenomena between competing commercial products. This theoretical perspective offers insights into economic dynamics and product adoption.

Harahap *et al.* (2023) explored the role of religious education in improving the work ethic of Micro, Small, and Medium Enterprises (MSME) owners. Their study provides valuable insights into factors influencing work ethic and the potential role of religious education. Suryawan *et al.* (2023) empirically proved the influence of relationships and service quality on guest loyalty in the hotel industry. Their findings contribute to understanding the factors affecting customer loyalty in the hospitality sector. Ogungbire and Pulugurtha (2023) investigated the perception of non-motorists toward autonomous vehicles after a fatal crash. Their study provides insights into how external events may influence attitudes towards emerging technologies. Hmoud *et al.* (2023) addressed the underdeveloped use of chatbots in the Arabic banking sector and examined the technological aspects affecting customer adoption. This study focuses on the specific challenges in the Arab world regarding chatbot applications.

Almrshed *et al.* (2023) analyzed the relative importance of dynamic capabilities in manufacturing SMEs, emphasizing the role of technology adoption in moderating innovative financial strength and customer satisfaction. Sun and Moon (2023)) applied DINESERV to a food brand, Shake Shack, shedding light on the accountability of DINESERV in understanding casual dining customer behavior. These studies collectively contribute to the understanding of customer churn prediction, technological adoption, and innovation across various industries, offering valuable insights for future research and practical implementations.

MATERIAL AND METHODS

The work done in this article was carried out on a computer with a 12th Gen Intel(R) Core(TM) i7-12700H 2.70 GHz processor, 16.0 GB RAM, and Windows 10 operating system, using version 3.11.4 of the Python programming language.

Dataset

In this study, the Kaggle "cell2cell" dataset was used (Amin 2024). The relevant data set includes 58 parameters from 71,047 customers. With the data pre-processing techniques applied to the dataset, these values were transformed into 50,137 customer numbers and 55 parameters. In the first examinations made on the data set 7.,2% of customers continued their subscriptions, while 28.8% terminated their subscriptions.

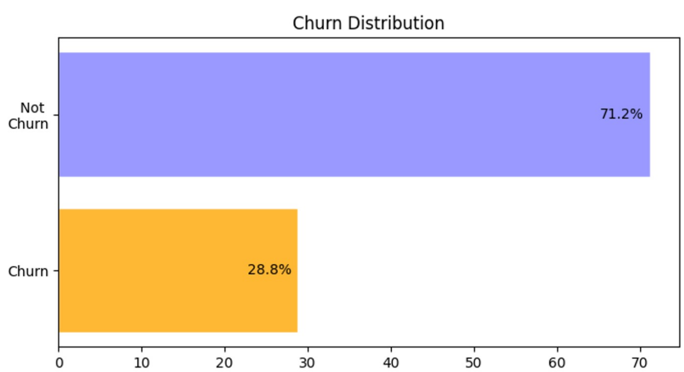

Figure 1 Churn or not churn distribution

In another analysis, the Correlation method was used to see the relationship between the parameters and the results were visualized.

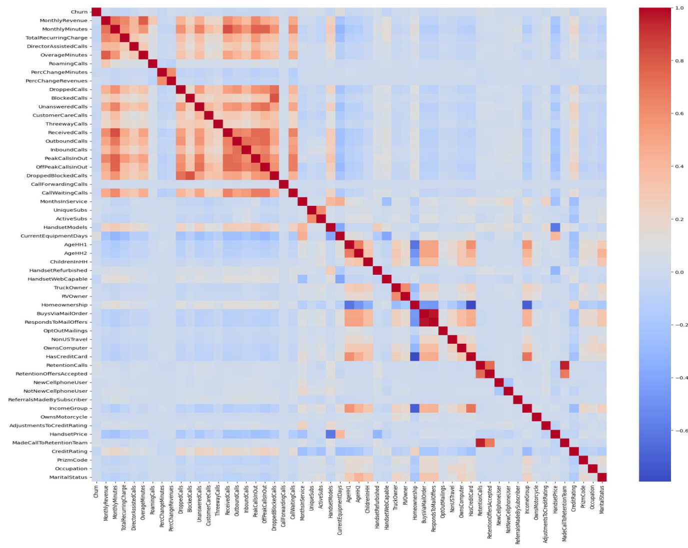

Figure 2 Relationship of parameters with correlation method

Data Pre-processing

In order to improve the quality of the data set, optimize model performance, and obtain clearer results, several processes were applied to the data set before moving on to the machine learning step. The parameters that did not impact the results, namely 'CustomerID,' 'ServiceArea,' and 'Handsets,' were removed from the dataset. As a result of this process, the initial 58 parameters were reduced to 55.

Empty cells in our dataset were filled out by calculating the average values in their respective columns. However, the procedure was deemed inappropriate for the cells in the 'Churn' column. Consequently, rows with empty cells in the 'Churn' column were excluded from the dataset. As a result of this process, the number of samples was reduced from 71,048 to 50,138. In another step of data pre-processing, numerical values were assigned to categorical data in the dataset to accommodate the requirements of machine learning algorithms, which inherently operate with numerical inputs. Specifically, the values 'No' and 'Yes' were transformed into '0' and '1'.

The data set underwent normalization, and it was noted that the parameters within the data set did not share the same maximum and minimum values. In order to address this disparity, the widely employed Min-Max Normalization method was utilized.

Min-Max Normalization It converts the values in the data set to values in the [0-1] range. The mathematical function of Min-Max Normalization is given below.

$$X_s = \frac{(x_i) - (x_{\min})}{(x_{\max}) - (x_{\min})} \tag{1}$$

Here, X_s is the normalized X value and takes values between $[0, 1]$. x_i is the original value, $x_{\min}$ is the minimum value in the data set, and $x_{\max}$ is the maximum value in the data set.

Machine Learning Algorithms

Machine Learning algorithms are computational models that allow users to make predictions or decisions based on data (Nahzat and Yağanoğlu 2021).

In this study, 11 different machine learning algorithms were examined. First of all, the data resulting from data pre-processing was divided into 80% training and 20% testing. The training data were trained on Linear Regression, Logistic Regression, Naive Bayes, Decision Tree, Random Forest, K-Nearest Neighbors, Gradient Boosting, Extreme Gradient Boosting, LightGBM, Adaptive Boosting, and CatBoost algorithms, respectively. Then, our models were tested on test data, and success criteria were examined. In the next section, the philosophy and mathematical approaches of the algorithms used are explained.

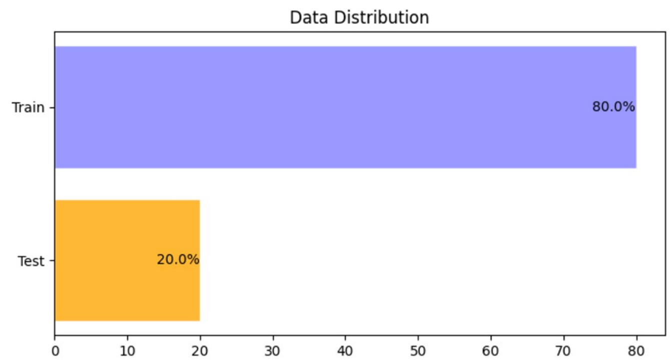

Figure 3 Train and test data distribution

Linear Regression Linear regression is used to find or predict the relationship between at least two parameters that have a cause-effect relationship between them. The general equation of linear regression is given below.

$$Y = Y_0 + m \cdot x \tag{2}$$

Here x is the selected independent variable; Y, predicted value; Y_0 is the point where the line intersects the y axis, and m is the slope of the line.

Logistic Regression Logistic Regression is a statistical method used to model the relationship of a dependent variable (usually categorical) with independent variables. The logistic regression function is given below.

$$P(Y|1) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 \cdot x_1 + \beta_2 \cdot x_2 + \cdots + \beta_k \cdot x_k)}} \tag{3}$$

In this function, $P(Y|1)$ represents the probability that the dependent variable is 1. e is the Euler number, which is the base of the natural logarithm (≈ 2.71828). β_0 is a constant term. $x_1, x_2, \ldots, x_k$ are the coefficients of the independent variable.

Naive Bayes Naive Bayes classifier is a supervised learning class algorithm that is widely used in fields such as data mining, machine learning, and emotion analysis (Şahinaslan *et al.* 2022).

The Naive Bayes algorithm makes the naive assumption that the independent variables are given together, which is why it is called "naive" (Orulluoğlu 2023). The Naive Bayes function is as follows:

$$P(C|X) = \frac{P(X|C) \cdot P(C)}{P(X)} \tag{4}$$

In this equation, $P(C|X)$ represents the probability that the class is at a particular data point. $P(X|C)$ represents the probability that a data point belongs to a particular class, given its observed properties. $P(C)$ represents the probability that the class is general. $P(X)$ represents the probability that the observed features are general.

The expression $P(X|C)$ is equal to the product of the probabilities determined by the class of each feature in the data point.

$$P(X|C) = P(X_1|C) \cdot P(X_2|C) \cdot \cdots \cdot P(X_n|C) \tag{5}$$

Here $X_1, X_2, \ldots, X_n$represent features in the data point.

Decision Tree A decision tree is a machine-learning algorithm that is used to solve classification and regression problems (Gülkesen *et al.* 2010). This algorithm tries to reach a conclusion through a series of decisions by analyzing the features in the data set.

The general formula of decision trees is as follows:

$$f(x) = \sum_{m}^{M} c_m \cdot \mathbb{I}(x \in R_m) \tag{6}$$

In this equation, $f(x)$ refers to the predicted output for the input feature vector x. M represents the total number of nodes in the tree. R_m refers to the region at node m. $\mathbb{I}(x \in R_m)$ is the indicator function, which takes the value 1 if x belongs to the region R_m, and 0 otherwise. c_m refers to the estimated value at node m.

Random Forest Random Forest is an ensemble learning algorithm that combines multiple decision trees (Özdemir 2018). The main idea behind the mathematical formula of the Random Forest model is to combine the predictions of each decision tree and average them or make a vote. The mathematical formula is given below (Equation 7).

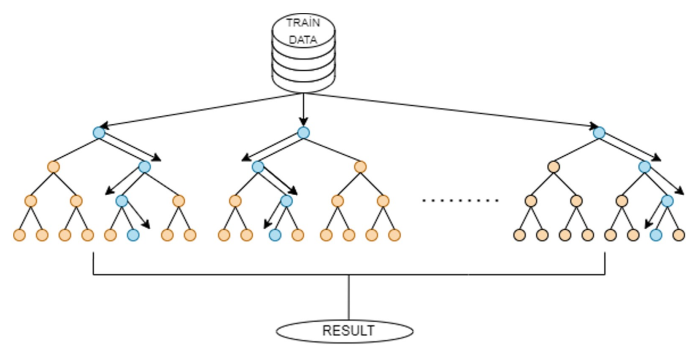

Figure 4 Random forest structure

$$f(x) = \frac{1}{N} \sum_{i=1}^{N} f_i(x) \tag{7}$$

In this formula, $f(x)$ represents the predicted target variable, N represents the total number of trees, and $f_i(x)$ represents the prediction of tree i for the input dataset x.

This formula takes the prediction of each tree, and then these predictions are averaged or voted to get the final prediction. This can help the model be more stable and perform better overall, as the error proneness of one tree can compensate for the errors of other trees. This algorithm also introduces randomness into the creation of trees, ensuring that each tree is different from each other.

K-Nearest Neighbors K-nearest neighbors is a classification and regression algorithm. The basic working principle consists of the training and prediction phase. In the training phase, the model learns the labeled dataset (Kılınç *et al.* 2016). In the prediction phase, when an unknown sample is given, it first finds its neighboring points and examines the labels of these points. In the case of classification, it uses the most repeated label as the prediction, while in the case of regression, it uses the average of the labels of the neighboring points as the prediction.

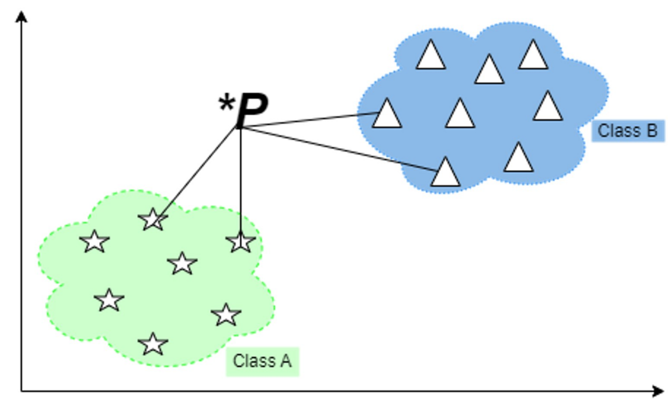

Figure 5 K-Nearest Neighbors algorithm

The mathematical formulas used by the K-Nearest Neighbors algorithm for classification are as follows:

$$\text{distance}(x, y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \tag{8}$$

$$\hat{y} = \arg\max_j \sum_{i=1}^{k} \mathbb{I}(y_i = j) \tag{9}$$

The Euclidean distance is found in Equation 8. In this equation, x and y are the vectors between the two samples, and n is the dimension of the vectors.

Equation (9) contains the mathematical expression that the algorithm uses to make a prediction by finding the neighboring points of the unknown sample and then classifying them through the labels of these points. In this formula, $\hat{y}$ is the predicted class, K is the number of neighbors, and y_i is the label of the i^{th} neighbor. $\mathbb{I}(\cdot)$ is the point representation function that takes the value 1 if the expression is true and 0 otherwise.

The article could contain subtitles where required, be written in scientific language, put thoughts together from diverse disciplines, combine evidence-based knowledge and logical arguments, and convey views about the aim and purpose of the article. It must address all readers in general. The technical terms, symbols, and abbreviations must be defined the first time they are used in the article.

Gradient Boosting Gradient boosting is a machine learning method and generally uses tree-based learning algorithms (Nusrat *et al.* 2020). It basically aims to create a strong prediction model by combining weak students.

Let it be a data set consisting of (x_i, y_i), $i = 1, 2, 3, \ldots, N$ points. Here, x_i represents the input features and y_i represents the target variable. The model's prediction is initially set to zero.

$$F_0(x) = 0 \tag{10}$$

A new prediction model is added at each iteration to minimize the error function:

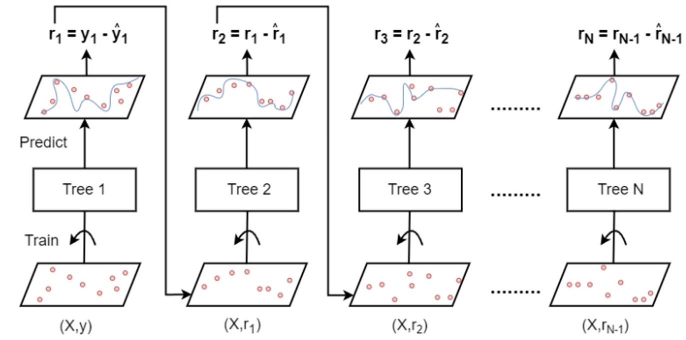

Figure 6 Gradient Boosting Algorithm.

$$F_m(x) = F_{m-1}(x) + \rho \cdot h_m(x) \tag{11}$$

In this Equation (11), m represents the number of iterations, ρ represents the learning rate, and h_m represents the newly added weak model.

With the aim of minimizing the error function, we choose Q using a specific loss function. When determining Q, optimization methods such as gradient descent are used. This is stated as follows:

$$h(x) = \arg\min_h \sum_{i=1}^{N} L\left(y_i, F_{m-1}(x_i) + \rho \cdot h(x)\right) \tag{12}$$

In this Equation (12), L refers to the $\arg\min_h$ function that will minimize the error function if the loss function is h.

The general formula for the prediction model would be:

$$f(x) = \sum_{i=1}^{N} h_i(x) \tag{13}$$

In this formula, $f(x)$ represents the prediction model and $h_i(x)$ represents the prediction value of each tree. In the training phase, a certain step size of each $h_i(x)$ gradient boosting algorithm is multiplied by ρ and added to the total.

Extreme Gradient Boosting (XGBoost) XGBoost is a machine-learning algorithm and a tree-based model. XGBoost is a federated model that combines a set of weakly learned decision trees. These trees are put together in a way that complements each other and corrects errors. XGBoost is often used to solve regression and classification problems (Korkmaz and Kaplan 2023). The mathematical equation of XGBoost can be written as follows:

$$\text{Objective Function} = L(\theta) + \Omega(\theta) \tag{14}$$

In this Equation (14), $L(\theta)$ represents the loss function and measures how much the model's predictions deviate from the true values. This can often include mean square error for regression or various loss functions for classification.

$$L(\theta) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) \tag{15}$$

In this Equation (15), n represents the total number of data points, y_i represents the true value of the i^{th} data point, $\hat{y}_i$ represents the model's prediction for the i^{th} data point, and $l(y_i, \hat{y}_i)$ represents the loss function for each data point. Mean square error

(Equation 16) for regression or cross-entropy functions (Equation 17) for classification can be used as loss functions.

$$L(\theta) = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{16}$$

$$l(y_i, \hat{y}_i) = -\left(y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)\right) \tag{17}$$

The other term of Equation (18), $\Omega(\theta)$, represents the regularization term and is used to control the complexity of trees. This term imposes punishment to limit the size and number of trees. This protects against overfitting.

$$\Omega(\theta) = \gamma T + \frac{\lambda}{2} \sum_{j=1}^{T} w_j^2 \tag{18}$$

In this equation, T represents the number of trees and w_j represents the node weights of the j^{th} tree. γ adds a regularization term to each tree and controls the addition of trees. λ controls the complexity of the tree by the square of the node weights.

The third term of the Equation (14), θ, represents the parameters of the model. These parameters include decision rules, weights, and other properties at the nodes of each tree.

LightGBM LightGBM is an implementation of the Gradient Boosting framework, a machine learning framework. Therefore, the mathematical formula of LightGBM is generally similar to the formula of Gradient Boosting algorithms. LightGBM stands out with features such as histogram-based learning and scaled gradient descent (Korkmaz and Kaplan 2023). Basically, the mathematical equation is:

$$F_m(x) = F_{m-1}(x) + \eta \cdot h_m(x) \tag{19}$$

In this equation, $F_m(x)$ is the sum of the prediction when m trees are added. $F_{m-1}(x)$, $m-1$ is the estimate with trees added. η represents the learning rate and $h_m(x)$ is the contribution of the m^{th} tree. LightGBM specifically uses histogram-based learning. In this way, the learning process accelerates and allows lower memory usage.

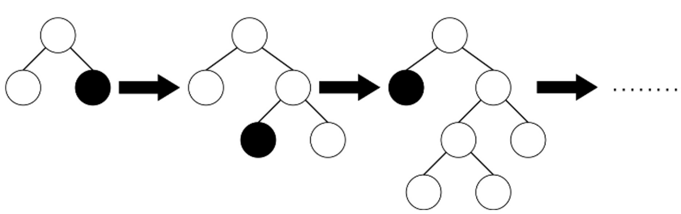

Figure 7 LightGBM structure.

Adaptive Boosting (AdaBoost) AdaBoost is an ensemble learning algorithm that creates a strong learner by combining a number of weak learners (Kul and Sayar 2021).

After training each student, thanks to its weighted error function, AdaBoost weights each example according to its misclassification rate. This error represents the difference between the actual label y_i and the predicted label $h_t(x_i)$.

$$\epsilon = \sum_{i=1}^{N} w_{(t,i)} \cdot \Pi\left(h_t(x_i) \neq y_i\right) \tag{20}$$

In this Equation (20), N is the data point, the t^{th} student, and $w_{(t,i)}$ is the weighting factor. $\Pi(\cdot)$ representation is the Indicator Function.

$$\alpha_t = \frac{1}{2} \ln\left(\frac{1-\epsilon_t}{\epsilon_t}\right) \tag{21}$$

In this formula (Equation 21), ϵ_t represents the weighted error rate (Equation 20). With this formula, each student is assigned a weight. These assigned weights depend on the student's achievement.

The following formula is used to update the weights:

$$w_{t+1,i} = \frac{w_{t,i} \cdot e^{-\alpha_t \cdot y_i \cdot h_t(x_i)}}{Z_t} \tag{22}$$

Here, Z_t is the normalization factor, which ensures that the weights sum to 1.

With the contributions of all students, a strong student is created with the following formula:

$$H(x) = \text{sign}\left(\sum_{t=1}^{T} \alpha_t \cdot h_t(x)\right) \tag{23}$$

In this way, AdaBoost combines a number of weak students to create a strong student.

CatBoost CatBoost is a Gradient Boosting algorithm designed to deal with categorical variables. CatBoost is basically an ensemble learning model created by combining many decision trees (İpek 2021).

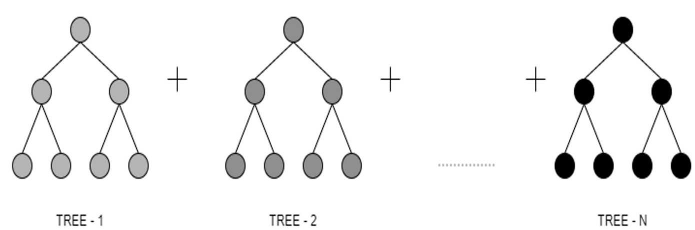

Figure 8 CatBoost structure.

The main components of CatBoost are the Objective Function, Decision Trees, and Gradient Boosting Algorithm. In addition, it has a special structure that processes categorical variables. Thanks to this structure, more effective processing is achieved by using the internal order of categorical variables.

Success Metrics

Various metrics are used to evaluate the success of machine learning algorithms. These metrics help us understand how well a model is performing and measure the model's predictive capabilities. In this study, the philosophy and mathematical approaches of five different success criteria are given. The success of 11 different algorithms used was examined according to these success criteria.

Confusion Matrix A complexity matrix is used to interpret the results of an established classification model and to cross-examine the errors in the relationship between real and predicted values.

- **True Positive**: Correctly predicting the positive situation.
- **True Negative**: Correctly predicting the negative situation.
- **False Positive**: Incorrectly predicting the positive situation.
- **False Negative**: Predicting the negative situation incorrectly.

Table 1 Confusion Matrix

Confusion Matrix		Actual Values	
		Positive (1)	Negative(0)
Predicted Results	Positive (1)	TP [1,1]	FP [1,0]
	Negative(0)	FN [0,1]	TN [0,0]

Accuracy, Precision, Recall, F1-score These scores are derived from the confusion matrix and allow us to see the success of the model more clearly.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{24}$$

$$\text{Precision} = \frac{TP}{TP+FP} \tag{25}$$

$$\text{Recall} = \frac{TP}{TP+FN} \tag{26}$$

$$\text{F1-Score} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{27}$$

eXplainable Artificial Intelligence (XAI)

Explainable artificial intelligence (XAI) refers to a set of processes and methods that aim to provide a clear and understandable explanation for the decisions offered by machine learning (ML) models.

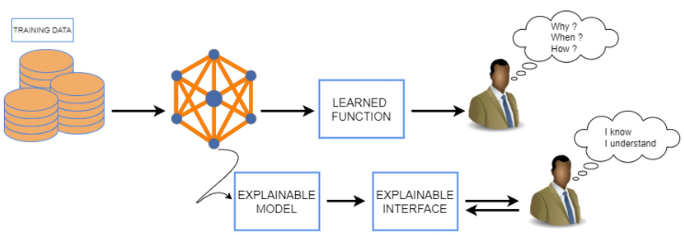

Figure 9 XAI Structure.

XAI architecture depends on specific approaches and methods used to provide transparency and interpretability in the machine learning model. However, in general, the XAI architecture can be thought of as a combination of three basic components. These are the machine learning model, Description Algorithm, and Interface respectively (Gunning *et al.* 2019).

The machine learning model is the core component of XAI and represents the basic algorithms and techniques used to make predictions and inferences from data. The explanation algorithm is the XAI component of the model used to provide information about the most relevant and effective factors in the predictions. The interface component is used to present the information generated by the annotation algorithm to actors. In this study, XAI's two most popular algorithms were reviewed. The philosophical and mathematical approaches of these algorithms were explained.

LIME (Local Interpretable Model-agnostic Explanations) Lime is a popular XAI approach that uses the model's native approach to provide interpretable and explainable information about the factors most relevant and influential in the model's predictions.

The general mathematical expression of the LIME model is as follows:

$$\text{explanation}(x) = \arg\min_{g\in\mathcal{G}} (f, g, \pi_x) + \Omega(g) \tag{28}$$

In this equation 28, x is an instance being explained. The explanation of x is the result of the maximization of the fidelity term (f, g, π_x) with complexity of $\Omega(g)$. f represents a black-box model, which is explained by an explainer, represented by g (Knapič *et al.* 2021).

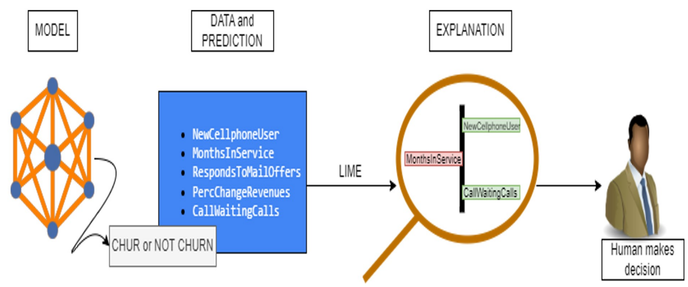

Figure 10 LIME structure.

The LIME algorithm generally follows the stages of categorizing numerical variables, obtaining new observations similar to the distribution of the data set, and determining the effects of the variables on the observation by developing an explainable model based on this data set (Garreau and von Luxburg 2020).

SHAP (SHapley Additive exPlanations) SHAP is an XAI approach and uses Shapley values derived from game theory to provide explainable information about the most important and influential factors in the model's predictions (Zhang *et al.* 2023; Feng *et al.* 2021). Shapley values come from cooperative game theory and are a concept that fairly measures a player's contribution. SHAP provides a framework for understanding how a model creates its predictions using these values.

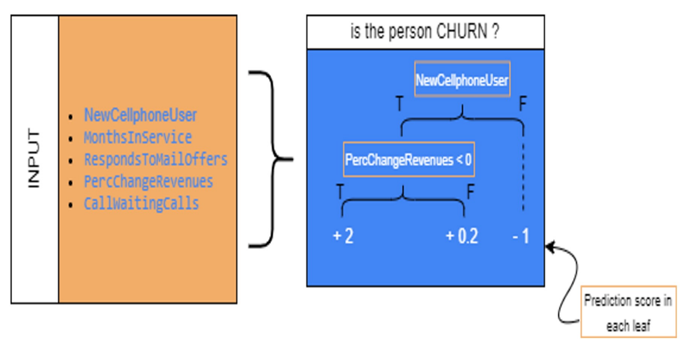

Figure 11 SHAP structure.

The mathematical equations of Shapley value (29) and SHAP (30) value are as follows:

$$\phi_i(v) = \frac{1}{|N|!} \sum_{S\subseteq N\setminus\{i\}} \frac{|S|! \cdot (|N|-|S|-1)!}{|N|!} [v(S\cup\{i\}) - v(S)] \tag{29}$$

In this equation (29), N represents the set of players and v represents a value function. $v(S)$ represents the value produced by coalition S. Each player's (i) Shapley value is the average of the player's values with the other players in the coalition.

$$\phi_i(f) = \frac{1}{N!}\sum_{\pi}\left[f(x_{\pi(i)}) - f(x_{\pi})\right] \quad (30)$$

In this equation (30), $f(x)$ represents the *output of the model* (where x is the input features). Here π represents all $N!$ permutations, and $x_{\pi(i)}$ is the π permutation of the i^{th} property of x. The SHAP value adapts Shapley values to understand the contribution of each parameter in creating a model's estimate.

RESULTS

The "cell2cell" dataset available on Kaggle was passed through the Data Pre-Processing methods mentioned above and divided into two (80% training, 20% testing) to be used in machine learning algorithms. The test data was passed through the algorithms, and the created models were tested on the test data. The success of the models was compared based on the accuracy score.

Table 2 Accuracy Score Table of Machine Learning Algorithms

ML Algorithms	Accuracy Score (%)
*LightGBM	73.085
CatBoost	73.045
Gradient Boosting	72.626
Random Forest	72.567
KNN	72.138
Linear Regression	72.138
AdaBoost	72.118
Logistic Regression	72.108
XGBoost	72.108
Decision Tree	61.836
Naïve Bayes	54.128

As a result of the examinations, the LightGBM algorithm became the best-performing model with an accuracy score of 73.085%. The outputs of this model were later announced together with the XAI algorithms. At this stage, XAI's two most popular algorithms were used. The results were visualized.

According to Figure 12, we saw that red (Churn) and blue (Not Churn) colors occupy half of the horizontal rectangles for each class. This means that each attribute has an equal impact on the label. But 'CurrentEquipmentDays' is the feature that has the most power. On the other hand, 'CustomerCareCalls', 'OffPeakCallsInOut' and 'RespondsToMailOffers' have the least power.

In Figure 13 and Figure 14 there is a summary chart of the Churn or Not Churn labels. In these graphs, the -y axis represents the features ranked according to their average SHAP values. While the -x axis represents SHAP values, positive values for a particular feature indicate that the model's prediction approaches the examined label. For example, in Figure 13, since the MonthlyMinutes feature is concentrated in positive values and this graph belongs to label number 1 (Churn), this feature approaches label number 1. We may not be able to make these inferences for some features. The SHAP algorithm also provides us with dependency graphs.

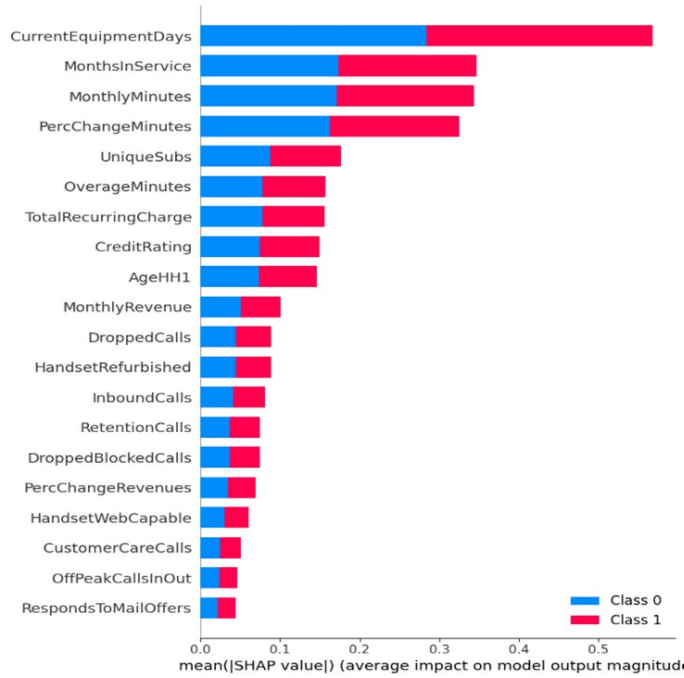

Figure 12 Variable importance graph.

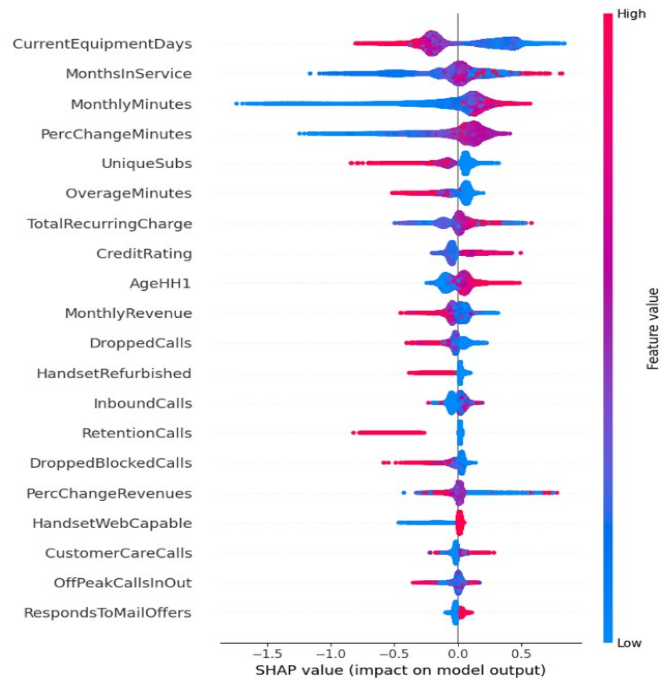

Figure 13 Summary chart of churn label (1).

We extract the information from the dependency graphs that we do not extract from the summary table.

Figure 15 shows the dependency graph of the 'CurrentEquipmentDays' feature. According to this graph, in cases where the 'CurrentEquipmentDays' value is higher than 0.2, the Churn is high. On the other hand, if this value is lower than 0.2, the Not Churn status is high.

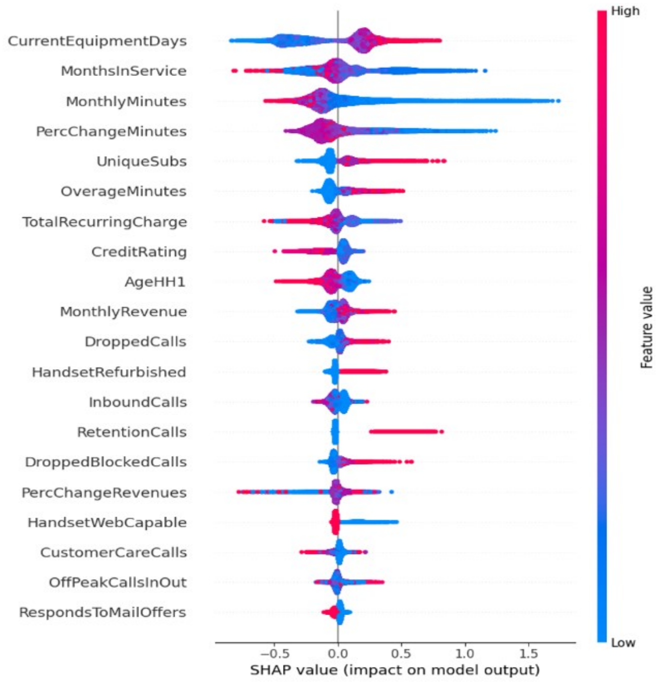

Figure 14 Summary chart of churn label (0).

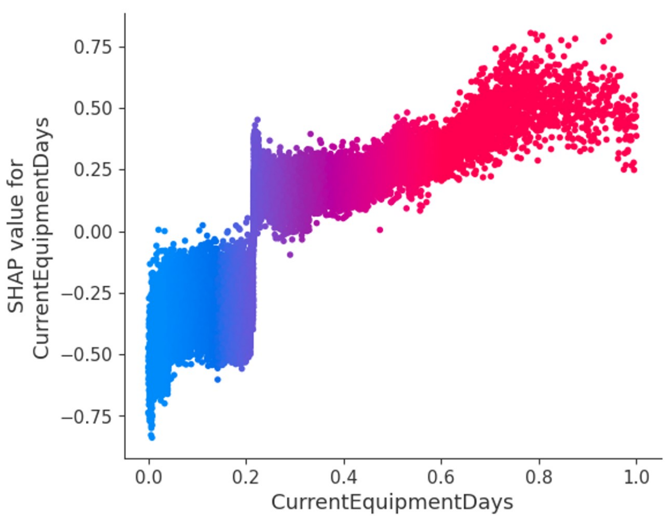

Figure 15 SHAP dependency chart of CurrentEquipmentDays parameter.

The results given by machine learning models are evaluated with the SHAP algorithm; first, the general effect of the parameters on the result was examined, then the class labels and the parameters that they affected the most were examined, and finally the effect of any parameter value on the result was examined. Another algorithm of XAI, LIME algorithm, explains the results by interpreting them locally, that is, it tries to explain the model's prediction for the samples in the dataset. The results of the LIME algorithm are given below. The results of LIME charts contain three main information from left to right. The leftmost information gives the predictions of the model, the middle information gives the contributions of the parameters, and the rightmost information gives the actual value of each feature.

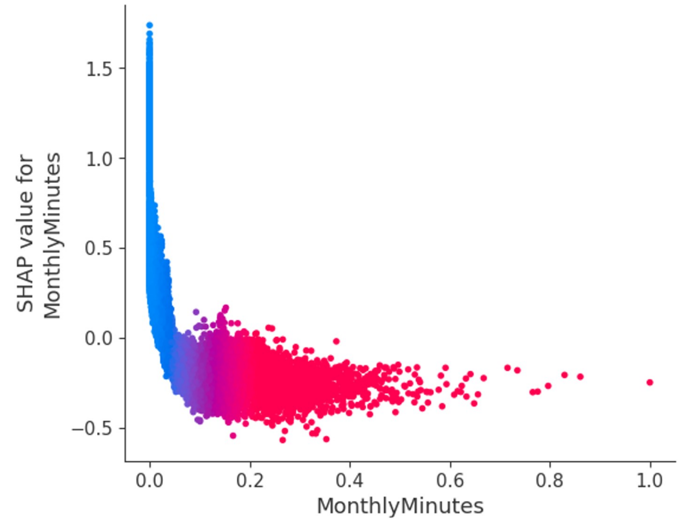

Figure 16 SHAP dependency chart of MonthlyMinutes parameter.

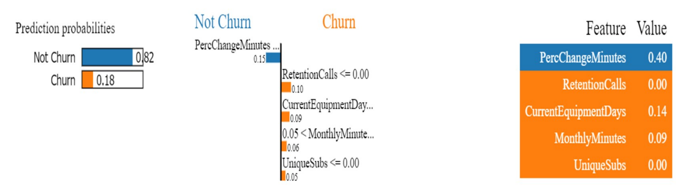

Figure 17 Results of the LIME Algorithm 1.

The information in this graph (Figure 17) shows the status of the 1000th person in the data set. According to this review, this person will not unsubscribe with 82.0% confidence.

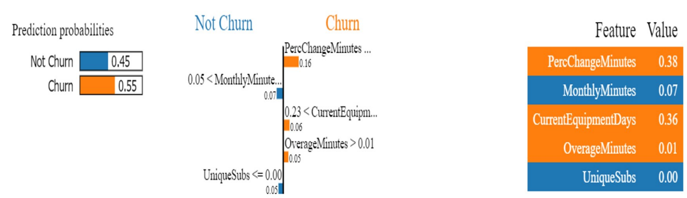

Figure 18 Results of the LIME Algorithm 2.

The information in this graph (Figure 18) shows the status of the 500th person in the data set. According to this review, this person will unsubscribe with 55.0% confidence.

CONCLUSION

Initially, a meticulous examination of the dataset was conducted. Identifying and eliminating parameters such as 'CustomerID,' 'ServiceArea,' and 'Handsets' that did not contribute significantly to the analysis resulted in a refined dataset comprising 55 parameters. Categorical variables were adeptly converted into numerical counterparts, and missing values, excluding the target variable, were filled with the mean of the respective parameter. Rows with missing values in the 'Churn' parameter were subsequently removed. Following these pre-processing steps, the dataset evolved into a robust set containing 55 parameters and 50,137 samples. Correlation analysis revealed no discernible linear relationships among the parameters.

The ’Churn’ variable was designated as the target, and the dataset was partitioned into 80% training and 20% testing sets. This stratification facilitated the evaluation of the new datasets using 11 diverse Machine Learning algorithms. Remarkably, LightGBM emerged as the top-performing model, boasting an impressive accuracy score of 73.085%. Other models, such as CatBoost and Gradient Boosting, closely followed with accuracy scores of 72.626% and Random Forest at 72.567%, respectively. Notably, ensemble algorithms exhibited superior predictive capabilities, surpassing similar studies and achieving commendable accuracy using the entire set of 55 features.

Subsequently, the interpretability of Machine Learning outcomes was elucidated using Explainable Artificial Intelligence (XAI) algorithms. Two XAI algorithms were employed, and the SHAP algorithm’s graphical representation unveiled the impact of each parameter on the target variable. Notably, ’CurrentEquipmentDays’ emerged as the most influential parameter, while ’CustomerCareCalls,’ ’OffPeakCallsInOut,’ and ’RespondsToMailOffers’ exerted minimal influence. A further exploration using SHAP highlighted that ’MonthlyMinutes’ predominantly influenced the ’1’ label, whereas ’MonthsinServices’ and ’PercChangeRevenues’ were impactful on the ’0’ label. This nuanced analysis underscored that monthly minute usage was a primary driver for customer churn.

Furthermore, dependency graphs provided by SHAP illustrated the relationship between parameters and results. For instance, if the value of the ’CurrentEquipmentsDays’ variable remained below 0.2, the risk of unsubscription was significantly lower. The interpretability exploration extended to LIME, another XAI algorithm. Examining the results with LIME for a specific customer (e.g., the 1000th customer) indicated an 82.0% confidence level that the customer was unlikely to unsubscribe.

Author Contributions

The author conceptualized and designed the study, conducted experiments, collected and analyzed data, and drafted the manuscript.

Availability of Data and Material

Not applicable.

Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this paper.

Financial Disclosure

Not applicable.

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Decision Making in Bank Personnel Selection Using the Analytical Hierarchy Process

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ABSTRACT Banks, like in many other areas, must make the right decisions in personnel selection. Incorrect personnel choices can lead to customer loss and increase internal organizational problems. Therefore, it is crucial for banks to make the right personnel selections and use objective criteria when making these decisions. Selecting the most suitable employee who can contribute to increasing the value of the organization from numerous applications requires a multi-stage process. Recent studies have observed that multi-criteria decision-making methods are frequently used in evaluating recruitment processes. In this regard, the Analytical Hierarchy Process (AHP) method is a tool that can assist banks in making accurate personnel decisions. The aim of the study is to identify the criteria used in personnel selection in banks and prioritize these criteria. In the research, key factors in the recruitment process include personal characteristics, organizational expectations, and experience as the main criteria. Using the AHP method, priority rankings of these factors have been made, and the most important criteria have been identified. The results highlight that determining the right criteria is crucial for enhancing the quality of the workforce and designing efficient recruitment processes in the banking sector. Furthermore, the AHP model provides a concrete tool for recruitment processes in the sector, helping decision-makers to make more informed and objective decisions.

KEYWORDS
Performance
AHP
Banking
Bank selection

INTRODUCTION

Banks are among the most important financial institutions in rapidly changing and developing free market economies. Banks are intermediary institutions that enable the transfer of resources collected from individuals and institutions with surplus funds (fund suppliers) to those in need of funds (fund demanders) as loans (Yetiz and Ergin Ünal 2018). In addition to collecting deposits and providing loans, banks contribute to national economies through a wide range of banking products and services. For example, creating book money to diversify payment instruments, conducting money transfer operations, assisting in the implementation of monetary and fiscal policies, and affecting income and wealth distribution are some of these contributions (Yetiz and Ergin Ünal 2018). When banks are established, like other businesses, they are considered to have an unlimited lifespan. Financial institutions wishing to sustain their sustainability by increasing their asset structure need to continuously improve their performance (Çamlıbel 2021).

There are many factors that affect performance. The banking sector, whose fields of activity expand every day, is one of the sectors where technology intensity is most prevalent. In today's banking, simply having advanced technology is not enough; it is also crucial to correctly select and utilize human resources. In banks, where technology, marketing, and human resources management converge, the aim is to meet customer demands with innovative approaches and to provide services required by globalization (Tüzün 2020). Therefore, competition between banks makes new investments inevitable.

In today's conditions, the ease with which many production factors can be imitated makes it difficult for businesses to differentiate themselves from their competitors. In the business and career world, where competitive advantage is focused on human capital, the process of selecting the workforce from qualified individuals has been considered a critical factor, increasing the importance of human resources, as in the rest of the world and in Turkey as well (Ekmekci 2018). Moving from this awareness, businesses today have shifted from a work-oriented production approach to one that centers on human beings. All businesses need financial and human resources to survive in their sector. It is widely accepted that optimal use of material resources in global markets depends on human resources (Öğüt *et al.* 2004).

One of the most fundamental functions of human resources management is the personnel selection process. This function serves the purpose of selecting personnel with appropriate qualifications for the right positions (Akoğlan Kozak 2012). Businesses research, find, select, and subject individuals with the most suitable characteristics to decision-making (hiring) processes (Acar 2013). In banking organizations, various criteria are sought in the selection of individuals for employment. When individuals with appropriate talents are placed in the right areas of activity, expectations for job productivity also increase (Yıldız 2023). In order to select a certain number of personnel, evaluations need to

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be made based on many variables. Some criteria are quantitative, while others are qualitative, requiring the use of techniques that can handle both together.

It is impossible to complete the selection process without ranking and comparing among numerous criteria. Through techniques called "multi-criteria decision-making methods," decision-making units can determine what is important and priority for their own organization. Thus, the complexity of potential problems in the process can be minimized (Diker 2021). Recruitment and personnel selection in the banking sector usually require a high level of expertise and attention. Candidates' suitability for the job is determined not only by technical knowledge and skills but also by personal traits and teamwork abilities. Therefore, an objective and systematic approach in the recruitment process is crucial. The Analytic Hierarchy Process (AHP) method is a frequently used technique in multi-criteria decision-making processes and can be effectively used in personnel selection in the banking sector.

AHP is a mathematical method that ensures an objective evaluation of a decision based on various factors. In this method, selection criteria are first determined, and each of these criteria is compared and weighted by the decision maker. Candidates are ranked according to the established criteria, and the most suitable candidate is selected. In the banking sector, the criteria generally include education level, experience, personal competencies (such as leadership and communication skills), cultural fit, and technical knowledge (Saaty 1980). In this study, criterion weights were established using the AHP method. Following the method developed by Saaty in the 1970s, face-to-face interviews were conducted with branch managers of relevant banks. Then, main criteria were identified and subjected to pairwise comparisons, and further pairwise comparisons were made among sub-criteria under the main criteria (Cheng *et al.* 2002).

The greatest advantage of the AHP method is that it minimizes subjective judgments in the decision-making process and ensures that each criterion is considered to the degree of its importance. In banks, this method provides transparency and consistency in the recruitment process. For example, candidates applying for a bank position can be scored based on the criteria determined by the AHP method, and their strengths and weaknesses can be objectively compared.

The aim of this study is to investigate the impact of different variables in personnel selection in the banking sector using the AHP method and to demonstrate the effectiveness of this method in human resources selection. The study was analyzed using the content analysis method, one of the qualitative research methods, and its sample consists of 9 banks. One-on-one interviews were conducted with branch managers of 9 banks operating in Çorum province, and each manager was asked pre-prepared interview questions. Data were collected based on the answers provided. To conduct a comparative study, frequency distributions were examined based on three main concepts emphasized most in the responses: "personal traits, institutional expectations, and experience."

Application of AHP Method and Recruitment Processes

The Analytic Hierarchy Process (AHP) is a widely used method for decision-making problems and is often preferred in multi-criteria decision-making problems. In the recruitment process, the AHP method allows the simultaneous consideration of various criteria to evaluate a candidate's suitability for the job. Candidates' different characteristics (such as experience, education level, skills, personal traits) are evaluated with varying weights, and the importance degree of each criterion is determined.

In many studies, differences among candidates have been analyzed objectively and systematically using the AHP method. This method is used to minimize human error in recruitment processes, evaluate candidates more efficiently, and make correct decisions.In the banking sector, recruitment decisions require consideration of numerous factors. Criteria such as candidates' experience, education levels, technical qualifications, communication skills, and personal traits are among the factors that should be considered in a bank's recruitment process. Each of these criteria may have different weights, increasing the complexity of the decision-making process. The Analytic Hierarchy Process (AHP) is a method that helps decision-makers select the most suitable candidate in such complex decision-making processes.

Advantages of Using the AHP Method in Recruitment

The use of the AHP method in the recruitment process offers many advantages. By minimizing the individual subjective assessments of decision-makers, it ensures a more objective and transparent process. Comparisons among candidates are made more precisely through numerical scoring. Additionally, determining different decision criteria (such as experience, education, personality fit, etc.) allows for more comprehensive analyses at every stage of the process. The multi-criteria structure of AHP makes the recruitment process fairer and more comprehensive.

Impact of AHP on Recruitment Processes

The use of AHP in recruitment processes has the following effects:

• Efficiency: Candidate evaluation can be conducted faster and more accurately.

• Error Rate: By reducing the tendency of HR experts to make subjective decisions, it allows for more accurate selections. When evaluating candidates, all criteria are reviewed on a numerical scale, reducing the margin of error caused by human factors in the decision-making process.

• Evaluation of Multiple Criteria: AHP allows for the simultaneous evaluation of multiple criteria. This ensures that many variables are taken into account, rather than focusing on just one factor in recruitment.

• Speeding Up the Decision-Making Process: Since comparisons between candidates are made numerically, the evaluation process occurs more quickly.

Additionally, clearly revealing the similarities and differences among candidates increases the accuracy of the recruitment process.

In line with the topic of the project, literature reviews were conducted on concepts such as recruitment and personnel processes in businesses and the banking sector, multi-criteria decision-making processes, and the Analytical Hierarchy Process (AHP) method. The researcher initiated the process of preparing scientific knowledge related to the topic through literature reviews prior to the interviews. This allowed the scientific process to proceed more systematically once the fieldwork for the interview began. Several academic studies have explored how the AHP method can be integrated into recruitment processes: Ho *et al.* (2009) emphasized that AHP can be effectively used not only in recruitment decisions but also in employee performance evaluations, promotion decisions, and determining compensation policies. Human resources departments can make more informed choices by using AHP in strategic decision-making processes.

Tsai and Chou (2010) integrated the AHP method into a recruitment evaluation model. In this study, considering numerous candidates and criteria, performance evaluations were conducted for each candidate, and the most suitable candidate was selected. AHP was highlighted as an ideal method for more accurately ranking candidates and reaching the outcome. Yılmaz and Şen (2014) stated that using the AHP method in recruitment helps decision-makers make more rational and systematic decisions. It was concluded that evaluating candidates across multiple criteria would make the process more objective, allowing HR managers to minimize subjective decisions.

Ünlü and Erdem (2015) pointed out that AHP is a method that evaluates not only numerical data but also expert opinions. This characteristic makes AHP a powerful decision support system, especially in human resources management. Furthermore, the multi-criteria structure of AHP allows for the evaluation of multiple factors together while determining the weight of each criterion, providing flexibility for decision-makers. Aktaş and Demirtaş (2017) emphasized that AHP is an effective tool in recruitment, especially when there are many candidates, and that this method accelerates decision-making processes and ensures more accurate selections. Çetin and Tüfekçi (2017) stated that AHP can be used not only in recruitment but also in processes such as employee performance evaluation and career planning in banks. Thanks to its multi-criteria decision-making ability, AHP allows for the evaluation of bank employees across various performance criteria. It was emphasized that having the right skills in bank employees is crucial for customer satisfaction and operational efficiency within the bank. In this context, AHP provides an opportunity for bank human resources departments to make more effective decisions.

Büyükşahin and Çelik (2018) stated that AHP makes the recruitment processes in the banking sector more objective and systematic. Especially in personnel selection, which plays an important role in customer services, credit evaluation, and operational processes in banks, making the right decisions is vital. AHP enables decision-makers to evaluate each candidate from multiple perspectives by determining the weight of various criteria, allowing not only technical qualifications but also potential success in customer relations to be considered. Yılmaz and Koç (2019) emphasized that in recruitment processes in the banking sector, AHP ensures that personal and psychological differences among candidates are also evaluated correctly. In their study, it was shown how the personality traits and cultural fit of candidates influence recruitment decisions. AHP enables banks to obtain more efficient results by considering the right criteria.

Demirtaş and Eroğlu (2020) examined how decision support systems made with AHP make recruitment processes more effective in banks. They concluded that the AHP method is an effective tool for helping decision-makers make the right decisions. According to the researchers, since candidates are rated according to each criterion, the relationships between the criteria are clearly revealed. The study concluded that adopting a systematic approach to candidate selection reduces errors and increases the competitive advantage of banks in the sector. Kılıç and Şahin (2020) stated that AHP is a versatile tool in human resources management, particularly effective in performance evaluations, promotion decisions, and reward processes. In this study, it was emphasized that the results obtained through the AHP method provide decision-makers with a more objective approach.

MATERIALS AND METHODS

The research data were obtained using the "Semi-Structured Interview Method," a qualitative research method. A "interview form" was prepared by the researcher in accordance with the purpose and subject of the research, consisting of 10 open-ended questions, and sent to the ethics committee. After receiving approval, the interviews were conducted. For the interview questions, appointments were made with 9 branch managers from banks operating in the Çorum province, and the interviews were held within the banks' premises. Before the interviews, the researcher informed the participants about the interview and the research, and obtained their consent for audio recordings. The interviews lasted approximately 1 hour. Transcripts of the interviews were created and transcribed. After transcribing the audio recordings, key words were identified, and the frequency of these keywords' repetition was determined using the Content Analysis Approach.

RESULTS

This study is based on data obtained from face-to-face interviews with branch managers of nine different banks operating in the Çorum province. The interviews addressed topics such as the banks recruitment processes, the personal characteristics employees should possess, and experience requirements. The data obtained were divided into three main categories using the content analysis method: Personal characteristics (communication, teamwork, risk management, problem solving, technical skills), corporate expectations (adaptability, cost management, teamwork, work ethics and values, data analysis skills), and experience (participating in projects, previous work experience, customer service and sales experience, internships). The frequency distribution of these key concepts, determined based on the responses, was identified. Since all participants did not consider cost as an important factor, it was excluded from the evaluation. This indicates that the salary paid to bank employees does not hold significant importance.

Table 1 shows the results of the pairwise comparison matrix of criteria according to the AHP method. Each criterion was scored on the basis of its importance relative to the others, based on the answers of the branch managers. Communication skills (18.00) and technical skills (16.00) have the highest total values, indicating that they are the most critical factors in personnel selection. In contrast, teamwork skills and risk management skills, with total weights of 2.64, have the lowest values and are considered relatively less important. The matrix systematically analyzes the decision-maker's preferences and determines the importance level of each criterion.

$$CI = \left(\frac{\frac{25.03}{5} - 5}{4} \right) = 0.001480051 \tag{1}$$

Random Inconsistency: 1.12

Consistency Ratio: $\frac{0.001480051}{1.12} = 0.001321475$

The *Wi* column in the table shows the weights of the criteria, while the calculations of $a_{ij}w_j$ and $\frac{a_{ij}w_j}{w_i}$ were used to check the consistency of the criteria. The consistency ratio was calculated to be 0.00134. Since this ratio is well below 10%, it indicates that the comparisons are consistent and that the decision-making process has been carried out reliably. This table clearly demonstrates that the decision-making process is systematic, objective, and consistent.

Table 2 contains the normalized weights and consistency ratio calculations for the 'personal characteristics' criterion according to the AHP method. The normalized values show each criterion's share within the total. Communication skills (38%) and technical skills (34%) have the highest weights, making them the most important criteria for personnel selection. In contrast, teamwork skills (6%) and risk management skills (6%) have the lowest weights. Problem-solving skills, with a weight of 17%, are of medium importance.

Table 1 Pairwise Comparison Matrix for Personal Characteristics

Personal Characteristics	Communication skills	Teamwork skills	Risk management skills	Problem-solving skills	Technical skills	TOTAL
Communication skills	1.00	7.00	7.00	2.00	1.00	18.00
Teamwork skills	0.14	1.00	1.00	0.33	0.17	2.64
Risk management skills	0.14	1.00	1.00	0.33	0.17	2.64
Problem-solving skills	0.50	3.00	3.00	1.00	0.50	8.00
Technical skills	1.00	6.00	6.00	2.00	1.00	16.00
TOTAL	2.79	18.00	18.00	5.67	2.83	47.29

Table 2 Normalized Table and Consistency Level Calculation (Personal Characteristics)

Personal Characteristics	Communication skills	Teamwork skills	Risk management skills	Problem-solving skills	Technical skills	Wi	aij wj	aij wj/Wi
Communication skills	0.36	0.39	0.39	0.35	0.35	0.38	1.84	4.83
Teamwork skills	0.05	0.06	0.06	0.06	0.06	0.06	0.28	4.99
Risk management skills	0.05	0.06	0.06	0.06	0.06	0.06	0.28	4.99
Problem-solving skills	0.18	0.17	0.17	0.18	0.18	0.17	0.86	5.11
Technical skills	0.36	0.33	0.33	0.35	0.35	0.34	1.73	5.11
TOTAL	1.00	1.00	1.00	1.00	1.00	1.00	4.99	25.03

Table 3 Pairwise Comparison Matrix for Corporate Expectations

Corporate Expectations	Adaptability	Teamwork	Business Ethics and Ethical Values	Data Analysis Skills	TOTAL
Adaptability	1	2	1	5	9
Teamwork	0.5	1	0.33	2	3.83
Business Ethics and Ethical Values	1	3	1	6	11
Data Analysis Skills	0.2	0.5	6	1	7.7
TOTAL	2.7	6.5	8.33	14	31.53

Table 3 provides the results of the pairwise comparison matrix for 'institutional expectations' using the AHP method. Each criterion has been scored based on its relative importance compared to the others. Work ethic and ethical values (11.00) and adaptability (9.00) have the highest total values, indicating that they are the most critical factors in personnel selection. Data analysis skills, with a score of 7.7, hold the third-highest importance, while teamwork, with a total value of 3.83, is considered relatively less important. The matrix systematically analyzes the decision-maker's preferences and determines the importance level of each criterion.

$$CI = \left(\frac{\frac{31.15}{4} - 4}{3} \right) = 1.2625 \tag{2}$$

Random Inconsistency: 0.58
Consistency Ratio: $\frac{1.2625}{0.58} = 2.1767$

The *Wi* column in the table shows the weights of the criteria, while the calculations of $a_{ij}w_j$ and $\frac{a_{ij}w_j}{w_i}$ were used to check the consistency of the criteria. The consistency ratio was calculated to be 2.1767. Since this ratio is well above 0.1, it is unacceptable, indicating that institutional expectations vary across banks. As a result, the 'institutional expectations' criterion is deemed unsuitable.

Table 4 contains the normalized weights and consistency ratio calculations for the institutional expectations criterion. The normalized values show each criterion's share within the total. Work ethic and ethical values (35%) and adaptability (29%) have the highest weights, making them the most important criteria for personnel selection. In contrast, data analysis skills (24%) and teamwork skills (13%) have the lowest weights.

Table 5 provides the results of the pairwise comparison matrix for the 'experience' criterion using the AHP method. Each criterion has been scored based on its relative importance compared to the others. Previous work experience (8.00), customer service experience, and sales experience (7.00) have the highest total values, indicating that experience is one of the most critical factors in personnel selection. The candidate's involvement in projects holds the third-highest importance with a value of 5.5. The internship sub-criterion, with a total value of 2.83, is considered relatively less important.

$$CI = \left(\frac{\frac{26.15961}{5} - 5}{4} \right) = 0.057981 \tag{3}$$

Random Inconsistency: 1.12
Consistency Ratio: $\frac{0.057981}{1.12} = 0.051768506$

Table 4 Normalized Table and Consistency Level Calculation (Institutional Expectations)

Corporate Expectations	Adaptability	Teamwork	Business ethics and ethical values	Data analysis skills	Average (wi)	aij wj	(aij wj)/wi
Adaptability	0.37	0.31	0.12	0.36	0.29	2.07	7.177956
Teamwork	0.19	0.15	0.04	0.14	0.13	0.86	6.596557
Business ethics and ethical values	0.37	0.46	0.12	0.43	0.35	2.44	7.067279
Data analysis skills	0.07	0.08	0.72	0.07	0.24	2.43	10.3082

Table 5 Pairwise Comparison Matrix for Experience

Experience	Projects Involved	Previous Institutions	Customer Service Experience	Sales Experiences	Internship	TOTAL
Projects Involved	1.00	0.50	1.00	1.00	2.00	5.50
Previous Institutions	2.00	1.00	1.00	1.00	3.00	8.00
Customer Service Experience	1.00	1.00	1.00	1.00	3.00	7.00
Sales Experiences	1.00	1.00	1.00	1.00	3.00	7.00
Internship	0.50	0.33	0.50	0.50	1.00	2.83
TOTAL	5.50	3.83	4.50	4.50	12.00	30.33

Table 6 Normalized Table and Consistency Level Calculation (Experience)

Experience	Projects Involved	Previous Institutions	Customer Service Experience	Sales Experiences	Internship	Average (wi)	aij wj	(aij wj)/wi
Projects Involved	0.18	0.13	0.22	0.22	0.17	0.18	0.96	5.224316
Previous Institutions	0.36	0.26	0.22	0.22	0.25	0.26	1.38	5.224007
Customer Service Experience	0.18	0.26	0.22	0.22	0.25	0.23	1.19	5.247272
Sales Experiences	0.18	0.26	0.22	0.22	0.25	0.23	1.19	5.247272
Internship	0.09	0.09	0.11	0.11	0.08	0.10	0.50	5.216746

The *Wi* column in the table shows the average of the criteria, while the calculations of $a_{ij}w_j$ and $\frac{a_{ij}w_j}{w_i}$ were used to check the consistency of the criteria. The consistency ratio was calculated to be 0.051768. Since this ratio is below 10%, it is within an acceptable level. As a result, experience gained at previous workplaces is one of the criteria to be considered in the recruitment process. The identification of corporate experience and customer service experience as the top sub-criteria clearly indicates the intention to work with qualified personnel specialized in the banking field.

Table 6 contains the normalized weights and consistency ratio calculations for the 'experience' criterion. The normalized values show each criterion's share within the total. Experience gained at previous workplaces (26%), customer service experience (23%), sales experience (23%), involvement in projects (18%), and internship (10%) have been weighted accordingly.

CONCLUSION

This study addresses the problem of determining the criteria decision-makers rely on in the personnel selection process in the banking sector. The aim of the study is to create a decision support system for banking institutions operating in the sector by using the AHP method, one of the multi-criteria decision-making methods. Through interviews with branch managers, who hold positions relevant to the bank, three main criteria (personal characteristics, institutional expectations, and experience) and their sub-criteria were identified, which are believed to influence personnel selection. Saaty's scale of importance was used in the relevant comparisons while identifying the criteria (Saaty 1980). When the weights (importance ranking) of the criteria affecting personnel selection were calculated, it was found that "communication skills" and "technical skills" within the personal characteristics criterion have the largest share in candidate preference. This was followed by "problem-solving skills," "teamwork," and "risk management skills."

The banking sector is one of the industries where human interactions are most intense. As a result, the findings clearly indicate that a communication-focused selection process is inevitable. Furthermore, due to the rapid integration of digital banking into our lives, it can be concluded that individuals equipped with technical knowledge and skills will be given more attention. As for institutional expectations, it was determined that their impact is much lower compared to the other main criteria due to their variability from one institution to another. This situation can be explained by the existence of many different departments in banks and the fact that employees are placed in positions through institutional exams, with promotions occurring based on employment success rates. According to the analysis results, "work ethic and ethical values" emerged as the most important sub-criteria within the institutional expectations main criterion. This was followed by "adaptability" and "data analysis skills," with "teamwork" being ranked last. As with all sectors and businesses, the issue of ethics and morals also shows its significance in the importance ranking for banks.

The honesty of individuals and their adherence to moral values is considered one of the factors banks pay attention to when selecting candidates, as it is crucial for developing an efficient work discipline. When evaluating the "experience" main criterion in personnel selection, it was concluded that the three sub-criteria with the largest share are "experience gained at previous institutions," "customer service experience," and "sales experience." "Involvement in projects" and "internship" were identified as secondary sub-criteria with less importance. The high impact of work experience is due to the dynamic nature of banks' business structure and the ease with which experienced individuals can adapt to the process. Banks, which operate with the awareness that increasing their capital structure is possible through a customer-oriented organization, expect their employees to establish correct relationships with customers. In this sense, having sectoral experience in communication with customers is among the primary criteria in the recruitment process. It is believed that the results obtained from the interviews with the bank managers will influence the evaluations of human resources managers. After compiling the data from the interviews with the managers, decision matrices were created. The analysis led to the conclusion using the AHP method, which is one of the multi-criteria decision-making methods. The AHP method is an effective tool for making the recruitment process more systematic and objective, ensuring the selection of the right candidate.

The use of AHP in human resources management increases efficiency, reduces error rates, and ensures more rational decision-making. Additionally, AHP's multi-criteria decision-making ability allows for the consideration of numerous factors in recruitment. Therefore, it has been concluded that the AHP method can be effectively used in the bank personnel selection process. The problem addressed in this study could also be evaluated using different multi-criteria decision-making methods. By examining the results produced by different methods, personnel selection criteria can be continuously revised, contributing to increased efficiency in the sector.

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Conflicts of interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Ethical standard

The authors have no relevant financial or non-financial interests to disclose.

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IoT's Economic Impacts on Smart Cities

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ABSTRACT This article comprehensively examines the economic impacts of the Internet of Things (IoT) on smart cities. Smart cities aim to enhance sustainability, efficiency, and quality of life through the integration of IoT technologies. The economic benefits of IoT in various domains, such as infrastructure management, energy conservation, transportation optimization, and the improvement of public services, are elaborated. Furthermore, potential costs and challenges, including high initial investments, data security concerns, and workforce transformation, are discussed. Supported by a literature review and current case analyses, the article presents findings that highlight IoT's contributions to the economic structure of smart cities and the barriers encountered. In conclusion, it emphasizes that IoT technologies have the potential to stimulate economic growth in smart cities through proper strategic planning and policy support.

KEYWORDS
Internet of things
Smart cities
Sustainability

INTRODUCTION

With rapidly increasing urbanization rates, the global urban population, which currently stands at approximately 55 billion, is projected to rise to 68 billion by 2050 Nations (2018). This accelerated urbanization process brings significant challenges in areas such as infrastructure, energy, transportation, healthcare, and public services. Traditional urban management approaches struggle to meet these growing demands and fall short in terms of sustainability and efficiency (Neirotti *et al.* 2014). In this context, the concept of smart cities emerges as a solution to make cities more livable, sustainable, and economically efficient through the integration of technological innovations. At the core of smart cities lies the Internet of Things (IoT), which enables physical objects to communicate with each other and with central systems via the internet, facilitating data collection, analysis, and automation processes (Atzori *et al.* 2010). IoT technologies support the digital transformation of urban infrastructures, enabling more efficient resource management, reduced operational costs, and improved service quality (Gubbi *et al.* 2013).

The economic impacts of IoT in smart cities are multidimensional and complex. On the one hand, IoT technologies optimize resource utilization, promote energy savings, and enhance efficiency, thereby reducing costs (Porter and Heppelmann 2014). On the other hand, the establishment and maintenance of IoT infrastructure require high initial investments, incur additional costs related to data security and privacy, and drive transformations in the labor market (Zanella *et al.* 2014). A detailed examination of these economic impacts is crucial for ensuring the sustainability and economic success of smart cities.

The primary objective of this article is to analyze the economic impacts of IoT in smart cities comprehensively. To achieve this, the following research questions will be addressed:

- How do IoT technologies contribute to the economic efficiency of smart cities? Contributions to resource management and operational efficiency.
- What role does IoT play in creating new job opportunities and employment in smart cities? Emerging job sectors, employment opportunities, and labor force transformations.
- What are the costs and economic challenges associated with IoT integration? Initial investments, maintenance and upgrade expenses, data management costs.
- How are IoT's economic impacts observed in different smart city examples?

Research on IoT and smart cities reveals the broad impacts of these technologies on urban management. Batty *et al.* (2012) detailed how smart cities align with future urbanization trends and the role of IoT in this process. Atzori *et al.* (2010) explored the fundamental components of IoT and its potential benefits for smart cities. More recent studies have focused on the economic impacts of IoT, analyzing its contributions to sustainability and economic growth (Gubbi *et al.* 2013).

This article aims to fill gaps in the existing literature and provide a more comprehensive perspective on the economic impacts of IoT in smart cities. Specifically, it seeks to balance both the positive and negative economic effects and enhance its analysis through case studies of different smart cities. Moreover, this work aims to expand the limited research on the economic impacts of smart city projects in developing countries like Turkey. Figure 1 illustrates the diverse application areas of IoT, ranging from smart

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cities to healthcare and beyond. This transformation creates new opportunities for both the public and private sectors while also introducing various economic impacts and challenges.

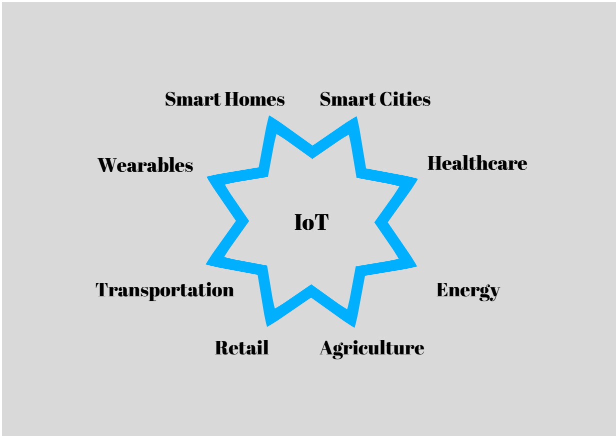

Figure 1 Applicaitons of IoT

This research offers valuable insights into the economic impacts of IoT in smart cities, providing city planners, policymakers, and the business community with essential knowledge. By addressing both the benefits and costs in a balanced manner, this study aims to enable more informed decision-making in the planning and implementation of smart city projects. Additionally, the analysis of different smart city examples contributes to identifying best practices and success factors. This facilitates the development of strategies and policies necessary to make smart cities sustainable and economically efficient.

MATERIALS AND METHODS

This section provides a detailed definition of the Internet of Things (IoT) and smart cities, followed by an examination of the relationship and interaction between these two concepts. This comprehensive review aims to better understand the role of IoT in smart cities and its economic implications.

Internet of Things

The Internet of Things (IoT) refers to a broad network of physical objects enabled by sensors, software, and other technologies to communicate with each other and central systems via the internet (Atzori *et al.* 2010). Core components of IoT include devices, connectivity infrastructure, data processing, and user interfaces (Gubbi *et al.* 2013). IoT is utilized across a wide spectrum of applications, from daily life to industrial environments, enhancing operational efficiency and enabling the emergence of new business models through its data collection and analysis capabilities (Madakam *et al.* 2015).

IoT operates through a system in which physical devices gather data via sensors, transmit it wirelessly to central servers, and analyze it to generate actionable insights (Zanella *et al.* 2014). This process enables real-time decision-making, automation, and process optimization. For example, smart thermostats optimize energy consumption, while smart meters monitor water and electricity usage to prevent resource waste (Ashton 2009).

These capabilities offer significant economic benefits not only to individual users but also to businesses and public institutions. The economic impacts of IoT manifest particularly in areas such as cost savings, efficiency improvements, new revenue models, and increased innovation capacity (Porter and Heppelmann 2014).

The Concept of Smart Cities Smart cities integrate information and communication technologies (ICT) to make urban management and services more efficient, sustainable, and citizen-focused (Batty *et al.* 2012). By leveraging technology across various domains, including infrastructure, energy, transportation, healthcare, security, and public services, smart cities aim to enhance quality of life (Caragliu *et al.* 2011).

The fundamental components of smart cities include data management, sustainability, participatory governance, and innovation (Neirotti *et al.* 2014). Data management involves analyzing city-wide data to inform decision-making processes. Sustainability covers topics such as energy efficiency, waste management, and environmental protection. Participatory governance encourages active citizen involvement in urban management, while innovation promotes the continuous development of new technologies and solutions (Hashem *et al.* 2016).

The success of smart cities typically relies on three key principles: technological infrastructure, data integration, and collaboration (Kitchin 2014). Technological infrastructure includes broadband internet, sensor networks, and data centers. Data integration ensures compatibility among datasets from various sources, while collaboration necessitates effective partnerships among public, private, and citizen stakeholders (Komninos 2013). Figure 2 illustrates the potential applications of IoT in smart cities, highlighting key areas such as energy management, transportation optimization, waste management, public safety, environmental monitoring, and smart infrastructure.

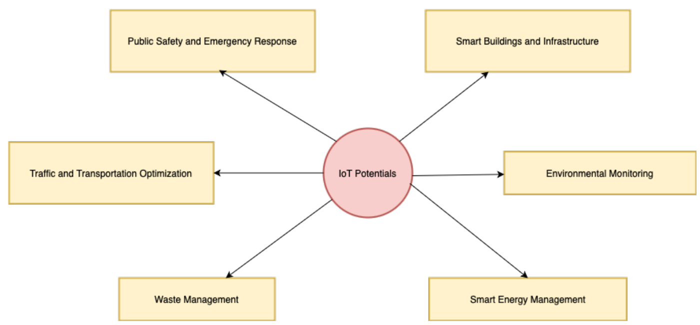

Figure 2 IoT potentials for smart cities

The Relationship Between IoT and Smart Cities IoT and smart cities are two interdependent and mutually reinforcing concepts. As a foundational element of smart cities, IoT enhances data collection and analysis capabilities citywide, enabling urban management to make more informed and effective decisions (Zanella *et al.* 2014). This integration increases operational efficiency in various sectors while delivering economic benefits (Gubbi *et al.* 2013).

Efficiency and Cost Savings: IoT applications in smart cities optimize resource management. For instance, smart energy management systems monitor and optimize energy consumption to save costs (Ahvenniemi *et al.* 2017). Smart transportation systems regulate traffic flow, reducing fuel consumption and minimizing time loss (Shaheen and Cohen 2013).

New Business Opportunities and Employment: The integration of IoT technologies creates new business opportunities and increases employment. Smart city projects generate job opportunities in areas such as data analysis, cybersecurity, software development, and IoT device maintenance (Manyika *et al.* 2015).

Revenue Growth and Economic Development: IoT-driven innovations enable the emergence of new business models and services, contributing to local economies and fostering economic growth. For example, smart healthcare applications enhance public health outcomes and create new employment opportunities in the healthcare sector (Hollands 2008).

Sustainability and Environmental Impacts: IoT facilitates achieving sustainability goals in smart cities. Smart water management systems ensure efficient use of water resources, while smart waste management systems improve waste collection and processing efficiency (Bibri 2018). These applications reduce environmental costs while helping cities meet sustainability objectives.

Data Security and Privacy: The use of IoT in smart cities involves collecting and processing large volumes of data, leading to significant challenges in data security and privacy. These challenges increase economic costs and necessitate additional security measures to prevent data breaches (Roman *et al.* 2013). In summary, the relationship between IoT and smart cities enhances efficiency, sustainability, and livability while fostering economic growth and innovation. However, it is crucial to address the challenges and costs associated with this integration through effective strategies and policies.

Economic Impacts:Positive Aspects This section provides an in-depth examination of the positive economic impacts of IoT technologies in smart cities. These impacts are generally categorized into efficiency improvements, cost savings, the emergence of new job opportunities, revenue growth, and technological innovations.

Efficiency Improvements and Cost Savings: One of the most significant advantages of IoT technologies in smart cities is the enhancement of operational efficiency and reduction of costs. Data collected through sensors and connected devices enables the optimization of city services. For instance, smart lighting systems use real-time data to minimize energy consumption by automatically adjusting light levels, resulting in significant energy savings (Ahvenniemi *et al.* 2017). Similarly, smart water management systems monitor usage, detect leaks early, and prevent water waste (Bibri 2018).

In addition, smart transportation systems regulate traffic flow, reducing fuel consumption and shortening travel times. These systems provide cost savings for both individual users and public transportation networks (Shaheen and Cohen 2013). Smart waste management systems optimize garbage collection processes, reducing costs and increasing the efficiency of waste management (Batty *et al.* 2012). Emergence of New Job Opportunities and Employment: The integration of IoT technologies in smart city projects leads to the creation of new job opportunities and an increase in employment. Fields such as data analytics, cybersecurity, software development, and IoT device maintenance and management offer new career prospects (Manyika *et al.* 2015). For example, data analysts play a critical role in managing and analyzing IoT device data streams within smart city projects (Porter and Heppelmann 2014).

Moreover, the widespread adoption of IoT technologies fosters collaboration between the public and private sectors. This collaboration encourages the development of new business models and partnerships, promoting the emergence of innovative ventures that contribute to economic growth (Gubbi *et al.* 2013). Revenue Growth and Economic Development: Innovative solutions offered by IoT enable the development of new business models and services, contributing to local economies and driving economic growth. IoT applications in smart cities improve efficiency in sectors such as energy, healthcare, transportation, and public safety, revitalizing economic activity in these areas (Hollands 2008).

For example, smart healthcare applications make healthcare services more accessible and effective, improving public health outcomes and creating new job opportunities in the healthcare sector (Zanella *et al.* 2014). Additionally, IoT-powered data analytics enables businesses to make informed decisions and optimize market strategies, contributing to increased revenue (Neirotti *et al.* 2014). Innovation and Technological Development: IoT technologies continuously promote innovation and technological advancement in smart cities. IoT's data collection and analysis capabilities support research and development (RD) activities, enabling the creation of new technologies (Atzori *et al.* 2010). This strengthens the technological infrastructure of cities while enhancing their innovation capacities.

Innovative IoT solutions contribute to achieving sustainability goals while increasing economic competitiveness. For instance, smart energy management systems facilitate the efficient use of renewable energy sources, supporting the development of innovative solutions in the energy sector (Ahvenniemi *et al.* 2017).

Economic Impacts:Negative Aspects and Costs The economic impacts of IoT technologies in smart cities are not limited to positive aspects. Their integration also entails various costs and challenges. This section delves into the potential negative economic impacts and costs associated with IoT in smart cities.

High Initial Costs: The establishment of IoT infrastructure requires significant initial investments in smart city projects. The installation of sensors, connectivity infrastructure, data centers, and other equipment incurs high costs (Zanella *et al.* 2014). These expenses can pose a considerable financial burden, especially for developing cities, making project implementation more challenging (Ahvenniemi *et al.* 2017). Additionally, investments in standardizing and ensuring the compatibility of IoT devices also contribute to increased costs. Making devices from different manufacturers interoperable requires additional technical and financial resources (Gubbi *et al.* 2013).

Maintenance and Update Costs: The costs of IoT infrastructure are not limited to initial investments; ongoing maintenance, updates, and improvements also impose a significant financial burden. Regular maintenance of IoT devices, software updates, and ensuring system security require continuous investment (Roman *et al.* 2013). Furthermore, the rapid evolution of IoT technologies necessitates regular updates and replacements of existing systems. This creates additional costs for city administrations and complicates budget planning (Porter and Heppelmann 2014).

Workforce Transformation and Social Costs: The integration of IoT technologies can lead to increased automation and the elimination of certain jobs, resulting in workforce transformations and job losses in specific sectors (Zanella *et al.* 2014). Low-skilled workers, in particular, may be adversely affected by automation processes driven by IoT, potentially leading to higher unemployment rates (Neirotti *et al.* 2014). Such transformations can exacerbate social costs, creating economic inequalities within societies. To address workforce transformations, retraining programs and opportunities for professional development are essential (Hashem *et al.* 2016).

Data Management and Privacy Costs: The use of IoT technologies in smart cities involves collecting and processing large volumes of data. Managing, storing, and securing this data incurs substantial costs (Roman *et al.* 2013). Technological solutions and security measures required to ensure data security and privacy create additional financial burdens for city administrations. Moreover, data breaches and cyberattacks can result in both economic losses and reputational damage. Therefore, continuous investments in data security and privacy are critical for ensuring the economic sustainability of cities (Porter and Heppelmann 2014).

Legal and Regulatory Challenges: The application of IoT technologies in smart cities also faces legal and regulatory challenges. Data protection laws in different regions may complicate the integration of IoT applications and lead to additional costs (Ahvenniemi *et al.* 2017). Furthermore, the lack of international regulations on the standardization and compatibility of IoT devices can limit intercity collaboration and data sharing (Gubbi *et al.* 2013).

Infrastructure and Technological Compatibility Issues:Successful integration of IoT technologies requires updating existing infrastructure to accommodate these new technologies. This process may involve renewing or completely replacing legacy systems, leading to additional costs and time requirements (Zanella *et al.* 2014). Ensuring compatibility among various IoT devices and platforms also presents technical challenges that can affect project feasibility (Gubbi *et al.* 2013).

Societal Acceptance and User Resistance: The successful adoption of IoT technologies depends on societal trust and acceptance. A lack of public confidence or resistance to new technologies can negatively impact the economic efficiency and success of projects (Neirotti *et al.* 2014). Addressing these issues may require additional educational programs and awareness campaigns, which can lead to extra costs (Hashem *et al.* 2016).

Application Areas This section provides a detailed examination of the various application areas of the Internet of Things (IoT) in smart cities and presents case studies of successful projects within these areas. The application areas include transportation and traffic management, energy management, waste management, public safety and emergency management, as well as healthcare and social services.

Smart transportation systems leverage IoT technologies to optimize traffic flow, improve public transportation efficiency, and reduce carbon emissions (Shaheen and Cohen 2013). For instance, smart traffic lights use real-time data analytics to monitor traffic congestion and automatically adjust light durations (Batty et al., 2012), thereby decreasing traffic jams and shortening travel times (Zanella *et al.* 2014). Smart energy management systems utilize IoT technologies to monitor and optimize energy consumption while integrating renewable energy sources (Ahvenniemi *et al.* 2017). Smart grids track energy distribution in real-time, balancing supply and demand and minimizing energy losses (Bibri 2018).

Smart waste management systems use IoT technologies to optimize waste collection, reduce waste volume, and increase recycling rates (Batty et al., 2012). Smart bins equipped with sensors monitor fill levels and optimize waste collection routes, improving the efficiency of waste management (Bibri 2018). Smart security systems enhance public safety and enable rapid response to emergencies using IoT technologies (Roman *et al.* 2013). IoT-based smart cameras, sensors, and data analytics play a critical role in crime prevention, incident response, and emergency management (Hashem *et al.* 2016). Smart healthcare applications use IoT technologies to make healthcare services more accessible and effective (Zanella *et al.* 2014). Remote health monitoring, smart devices, and data analytics allow continuous monitoring of patients' health and enable early interventions (Madakam *et al.* 2015).

Challenges and Barriers While the integration of the Internet of Things (IoT) into smart cities offers significant economic benefits, it also faces various challenges and barriers. This section examines the major obstacles and potential negative economic impacts associated with IoT in smart cities. Successful IoT integration requires a robust and compatible technological infrastructure. This process often necessitates updating or entirely replacing existing infrastructure to accommodate modern IoT technologies (Zanella *et al.* 2014). Integrating older systems with IoT devices can present technical challenges and incur additional costs (Gubbi *et al.* 2013). Furthermore, standardizing IoT devices and ensuring their interoperability require substantial engineering effort and financial investment. Ensuring that devices from different manufacturers work seamlessly together is a significant barrier during the integration process (Porter and Heppelmann 2014), leading to additional costs and time delays for city administrations (Ahvenniemi *et al.* 2017).

Establishing and maintaining IoT infrastructure involves substantial upfront costs. These include installing sensors, connectivity infrastructure, data centers, and other equipment (Zanella *et al.* 2014). For developing cities, these costs can pose a significant financial burden due to budget constraints (Ahvenniemi *et al.* 2017). Moreover, the return on investment (ROI) for IoT projects is often uncertain, raising doubts about their profitability (Manyika *et al.* 2015). This uncertainty may deter both public and private sector stakeholders from investing in IoT initiatives (Gubbi *et al.* 2013). The application of IoT technologies in smart cities brings regulatory and legal challenges. Data protection laws can complicate IoT integration and increase associated costs (Roman *et al.* 2013). Variations in data protection regulations across regions can further hinder intercity collaboration and data sharing (Ahvenniemi *et al.* 2017). Additionally, the lack of international standards for IoT device compatibility and standardization creates barriers to integration across cities (Gubbi *et al.* 2013). Such regulatory uncertainties pose significant challenges during the planning and implementation of IoT projects (Porter and Heppelmann 2014).

The use of IoT in smart cities requires the collection and processing of vast amounts of data, raising serious security and privacy concerns (Roman *et al.* 2013). Cyberattacks, data breaches, and malicious use of IoT systems threaten the security of IoT infrastructure (Hashem *et al.* 2016). Addressing these concerns requires city administrations to implement advanced security measures and technological solutions. Maintaining data security involves continuously updating security protocols and infrastructure, which imposes significant costs and complicates budget planning (Porter and Heppelmann 2014). The successful adoption of IoT technologies depends on societal trust and acceptance. A lack of public confidence or resistance to new technologies can negatively impact the economic efficiency and success of IoT projects (Neirotti *et al.* 2014). Addressing these issues may require additional educational programs and awareness campaigns, further increasing costs (Hashem *et al.* 2016). Furthermore, insufficient public knowledge about IoT technologies can hinder their effective utilization and prevent projects from achieving their goals (Neirotti *et al.* 2014).

RESULTS

To effectively leverage IoT's economic impacts in smart cities and overcome the associated challenges, various strategic perspectives and recommendations must be developed. This section outlines the future role of IoT in smart cities and strategies to maximize its economic potential. Figure 3 illustrates future perspectives and strategic recommendations for leveraging IoT's economic impacts in smart cities. Key areas include technological advancements, such as AI integration, machine learning, and 5G connectivity, alongside strategic planning through long-term goals, resource allocation, and public-private partnerships. Sustainability efforts focus on energy efficiency, waste management, and renewable integration, while economic resilience is driven by diversified sectors, job creation, and IoT-driven innovations. This visualization highlights the interconnected strategies necessary to maximize IoT's potential in urban environments.

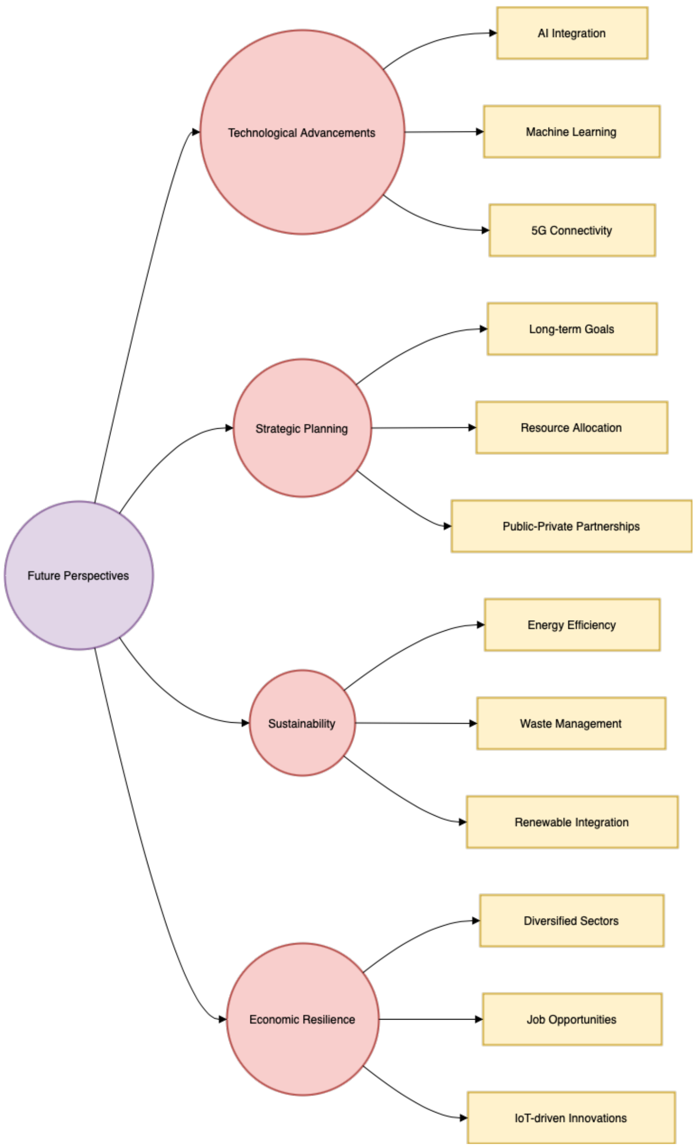

Figure 3 Future Perspectives of IoT

IoT technologies are expected to advance further, with innovative solutions emerging in the future. Integrating IoT with advanced technologies such as artificial intelligence (AI) and machine learning (ML) will enhance data analytics and decision-making processes in smart cities (Gubbi *et al.* 2013). These advancements will enable city administrations to make more informed and effective decisions, thereby improving economic efficiency (Porter and Heppelmann 2014). The proliferation of high-speed, reliable connectivity technologies such as 5G will also enhance the performance of IoT devices, increasing the success of smart city projects (Ahvenniemi *et al.* 2017).

Effective strategic planning and policymaking are essential to maximize IoT's economic impacts in smart cities. City administrations and policymakers should establish long-term goals for IoT projects and allocate the necessary resources to achieve them (Batty *et al.* 2012). Strong partnerships between public and private sectors should be established to ensure the financial and technical support needed for IoT projects. Such collaborations will enhance the success of IoT initiatives (Manyika *et al.* 2015).

To sustain IoT's economic impacts in smart cities, it is crucial to adopt principles of environmental and economic sustainability. IoT technologies can support sustainability goals such as energy efficiency, waste management, and the integration of renewable energy sources, thereby enhancing economic resilience (Ahvenniemi *et al.* 2017). Additionally, diversifying economic sectors within cities and creating new job opportunities through IoT-driven innovations can strengthen economic resilience (Porter and Heppelmann 2014). Strong public-private partnerships (PPPs) are vital for the successful implementation of IoT projects. Such collaborations provide the financial and technical support required for these initiatives (Gubbi *et al.* 2013). International collaborations and knowledge sharing can help identify best practices and success factors. Experiences gained from IoT projects in different cities can be applied to other cities, enhancing economic efficiency (Neirotti *et al.* 2014).

CONCLUSION

Our analysis demonstrates that ensemble models such as Random Forest and Gradient Boosting are highly effective in predicting customer purchase behavior. Logistic Regression, while simpler and more interpretable, provides lower accuracy and ROC AUC scores compared to ensemble models. Support Vector Machine and K-Nearest Neighbors offer robust alternatives, with KNN being particularly effective for datasets with a clear neighborhood structure. XGBoost, known for its efficiency and performance, also delivers excellent results. The insights gained from this study can help businesses make data-driven decisions, improve customer targeting, and design more effective marketing strategies. Additionally, this study contributes to the growing body of research on the application of machine learning in customer analytics, providing a reference for future studies and practical implementations.

Future studies could examine IoT's economic impacts in smart cities from a broader perspective and include more case studies. Research focusing on the economic effects of smart city projects in developing countries could expand the existing literature. Furthermore, studies exploring the sustainability impacts of IoT could provide valuable insights into enhancing cities' long-term economic resilience . Research on data security and privacy could help develop strategies to manage IoT's economic impacts more securely and sustainably . Finally, studies investigating the integration of advanced technologies such as AI and ML with IoT in smart cities could reveal the potential benefits and opportunities offered by these technologies, guiding future smart city projects.

Availability of data and material

Not applicable.

Conflicts of interest

The author declares that there is no conflict of interest regarding the publication of this paper.

Ethical standard

The author has no relevant financial or non-financial interests to disclose.

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Location-Based Technology for Real-Time Artifact Recognition in Businesses

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ABSTRACT The recognition of historical artifacts play a crucial role in sustaining cultural heritage and advancing tourism. Despite advancements in object detection technologies, accurately identifying artifacts in diverse geographical and environmental contexts remains a significant challenge. Existing models often struggle to adapt to region-specific features and the complexity of historical artifacts, limiting their practical applications. To address these limitations, this study evaluates the potential of YOLOv4, YOLOv7-X, and YOLOv9c models for historical artifact recognition, with a particular focus on location-based segmentation. Geographically distinct datasets were utilized for training and evaluation, enabling the models to achieve higher accuracy in region-specific artifact detection. Among the tested models, YOLOv9c demonstrated superior performance, achieving the highest metrics across accuracy (96%), precision (93%), recall (95%), and mean average precision (mAP, 71%), making it the best-performing model. These results highlight YOLOv9c's robustness and adaptability to complex datasets and diverse artifact characteristics. A user-friendly application interface was also developed, allowing real-time detection and providing detailed historical information about the artifacts. However, challenges such as the high computational cost of training YOLOv9c on high-resolution datasets were observed, particularly when compared to YOLOv4, which was computationally efficient but less accurate. YOLOv7-X offered a balance between performance and computational efficiency. The results demonstrate that location-based segmentation significantly enhances detection accuracy, making this approach highly effective for real-world applications in cultural heritage preservation and tourism.

KEYWORDS
Tourism technologies
Artificial intelligence
object detection
Artifact recognition
YOLO
Businesses

INTRODUCTION

Artificial intelligence (AI) plays a pivotal role in the digital transformation of the tourism sector by offering personalized experiences tailored to tourists' individual needs. AI-based mobile applications facilitate tourists' travel planning processes and optimize their itineraries. For instance, augmented reality and natural language processing integration in guiding services enriches the user experience by providing real-time information (Devlin *et al.* 2018; Zouni and Kouremenos 2008). Furthermore, object recognition algorithms serve as an important tool for promoting historical artifacts and cultural assets (Wang *et al.* 2025). In addition to mobile devices, compact computers with higher performance capabilities can also be utilized to handle computationally intensive AI tasks effectively, as demonstrated in studies on the effectiveness of machine learning models for various predictive tasks (Coşar and Kiran 2018; Deniz 2024). Blockchain technology has also been proposed to enhance data security and integrity in tourism-related autonomous systems, providing resilient solutions for location-based tasks, as shown in UAV applications (Cosar and Kiran 2021).

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AI also offers activity recommendations based on tourists' interests, which are continuously improved through user feedback (Molina-Collado *et al.* 2022; Loureiro *et al.* 2020). Specifically, genetic algorithms and machine learning methods in route planning optimize travel times and enhance visitor satisfaction (Homay *et al.* 2019). The use of AI in customer service has also become widespread, with intelligent chatbots answering frequently asked questions and making travel experiences more accessible for tourists (Kılıçhan and Yılmaz 2020).

Academic studies on the integration of AI in the tourism sector provide an in-depth analysis of the digital transformation in this industry. Seyfi et al. (Seyfi *et al.* 2025) analyzed the adoption processes of generative artificial intelligence technologies in the tourism sector, focusing on personal factors that influence tourists' travel planning decisions. Guan et al. (Guan *et al.* 2025) examined human-robot interactions and assessed the impact of AI-based robotic services on customer satisfaction. Rather (Rather 2025) investigated consumers' perceptions of AI-based technologies in terms of self-congruity and perceived value. Khairy et al. (Khairy *et al.* 2025) explored the effects of AI-supported leadership approaches aimed at enhancing green competitiveness and human capital. Moreover, Liu et al. (Liu *et al.* 2025) provided a framework for the application of machine learning techniques in sentiment analysis within tourism research.

In recent years, object recognition technologies have made significant progress, particularly with innovations in the YOLO (You Only Look Once) series of models. YOLOv7 (Wang *et al.* 2022) provides optimization in terms of speed and accuracy, effectively operating on mobile devices with low power consumption requirements. This model has become a standard for real-time applications and complex scene detection. A more advanced version, YOLOv9 (Wang *et al.* 2025), improves performance on large-scale datasets and has been adopted in various industries, including tourism, due to its enhanced features. Conversely, region-based algorithms such as Faster R-CNN (Ren *et al.* 2016) are preferred for projects requiring high precision, delivering effective results in detecting objects in tourist locations. In the study by Hilali et al. (Hilali *et al.* 2023), Faster R-CNN and YOLOv7 models were compared, revealing that Faster R-CNN excels in detailed scenes, while YOLOv7 offers advantages in speed.

Object recognition technologies play a vital role in promoting cultural heritage and natural sites in the tourism industry. Guidosse et al. (Guidosse *et al.* 2025) investigated the combined use of camera traps and AI technologies to monitor visitor activity in the Ardenne region of Belgium. Sánchez-Juárez et al. (Sánchez-Juárez and Paredes-Xochihua 2024) proposed a solution integrating object recognition algorithms into augmented reality (AR) projects to enhance tourists' interactive experiences. Shi et al. (Shi *et al.* 2024) developed the YOLOX network model to dynamically recognize tourist destinations in mountainous regions with complex scenes. Velvizhy and Sherly (Sherly and Velvizhy 2024) focused on AI-supported identification and speech transformation systems for religious figures, offering a new approach to preserving cultural heritage. Tsurcanu and Alexandrescu (Agapie *et al.* 2024) proposed a system using cloud-based object recognition solutions to optimize tourists' destination searches. Lu et al. (Lu *et al.* 2025) developed an autonomous campus tour guide vehicle, combining object recognition with LiDAR positioning to enhance the tourist experience.

In this study, the performance of object recognition algorithms was analyzed using selected artifacts from the İzmir region. The training dataset consisted of images from cultural heritage sites such as the House of the Virgin Mary, Ephesus Ancient City, and the Library of Celsus. Each artifact was captured from various angles, resulting in a total of 762 images, which were trained using YOLOv4, YOLOv7, and YOLOv9 models. The training process adopted a location-based approach, optimizing each artifact group on separate models. A four-fold cross-validation method was employed to evaluate the models' performance in terms of accuracy, precision, and recall.

The main contributions of this study are as follows:

- A location-based object recognition approach incorporating YOLOv4, YOLOv7, and YOLOv9 models has been proposed for the recognition of selected historical artifacts in İzmir.
- Comprehensive cross-validation methods have been applied to optimize the artifact recognition processes, and accuracy, precision, and recall metrics have been analyzed in detail for each model.
- The location-based training approach employed in this study enhanced regional recognition performance by modeling datasets obtained from different cultural regions.
- The high accuracy rates and real-time recognition capabilities of the YOLOv9 model have been demonstrated as a potential tool for the preservation and promotion of cultural heritage sites.

The rest of this paper is organized as follows: In the Proposed Methodology section, object recognition algorithms, location-based training strategy, cross-validation methods, and performance evaluation metrics will be explained. Next, the Data Collection and Preprocessing section will present the creation, labeling, and preparation of the dataset for model training. In the Experiments and Results section, the performances of YOLOv4, YOLOv7, and YOLOv9 models will be compared using various metrics, and the obtained findings will be analyzed in detail. The Discussion section will address the advantages and disadvantages of the location-based object recognition approach, as well as identify the limitations of the study and future research directions. Finally, the Conclusion section will summarize the main findings of the study and provide an overall assessment of the paper.

PROPOSED METHODOLOGY

This section summarizes the methodology employed in this study to achieve the research objectives. It provides a comprehensive explanation of the object recognition algorithms used, with a particular focus on the YOLO family and its variants. Additionally, the rationale behind adopting a location-based training strategy is explained, highlighting its potential to enhance the accuracy of object recognition in specific environments. Furthermore, the cross-validation techniques applied to ensure the robustness and generalizability of the models are discussed. Finally, this section details the performance evaluation metrics used to assess the effectiveness of the trained models.

Object Detection Algorithms

In this study, YOLOv4, YOLOv7-X, and YOLOv9c models were utilized for the recognition of historical artifacts. These models are advanced variants of the YOLO (You Only Look Once) family, optimized to meet real-time and high-accuracy requirements in object detection. Their architectural designs incorporate innovative techniques to maximize speed, accuracy, and computational efficiency.

YOLOv4 (Bochkovskiy *et al.* 2020) achieves an effective balance between accuracy and speed through its optimized architecture. It incorporates innovations such as the CSPDarknet53 backbone, Mish activation function, Self-Adversarial Training (SAT), and Cross Mini-Batch Normalization (CmBN). Additionally, the inclusion of the Spatial Pyramid Pooling (SPP) module enhances the model's ability to detect historical artifacts at various scales and in complex backgrounds.

YOLOv7 (Wang *et al.* 2022) is an extended variant designed to enhance the recognition performance of historical artifacts by utilizing the Efficient Layer Aggregation Network (E-ELAN) framework. This model applies expansion and reorganization techniques to optimize parameter usage and improve learning capacity. Moreover, its dynamic label assignment strategies refine training accuracy across multi-layer output heads. In this study, the YOLOv7-X variant was used.

YOLOv9 (Wang *et al.* 2025) represents the latest advancements in historical artifact recognition. It combines the General Efficient Layer Aggregation Network (GELAN) architecture with Programmable Gradient Information (PGI) mechanisms, effectively preventing information bottlenecks and ensuring the seamless propagation of features throughout the network. This model excels in the detailed and accurate classification and localization of historical artifacts. The YOLOv9c variant was employed in this study.

These models were selected due to their diverse strengths in artifact detection: YOLOv4 stands out for its speed and foundational innovations, YOLOv7-X excels with its extended architecture and flexibility, and YOLOv9c delivers superior performance with advanced gradient management and feature preservation mechanisms. The comparative performance metrics of the models are summarized in Table 1.

Location-Based Training Strategy

The location-based training strategy employed in this study aims to enhance the performance of object recognition algorithms in identifying historical artifacts by leveraging geographically specific datasets. This approach is designed to improve detection accuracy by training the models with data collected from various cultural and historical sites. Figure 1 illustrates the geographical distribution of the key regions used in the dataset, which include the House of the Virgin Mary, Ephesus Ancient City, and the Library of Celsus.

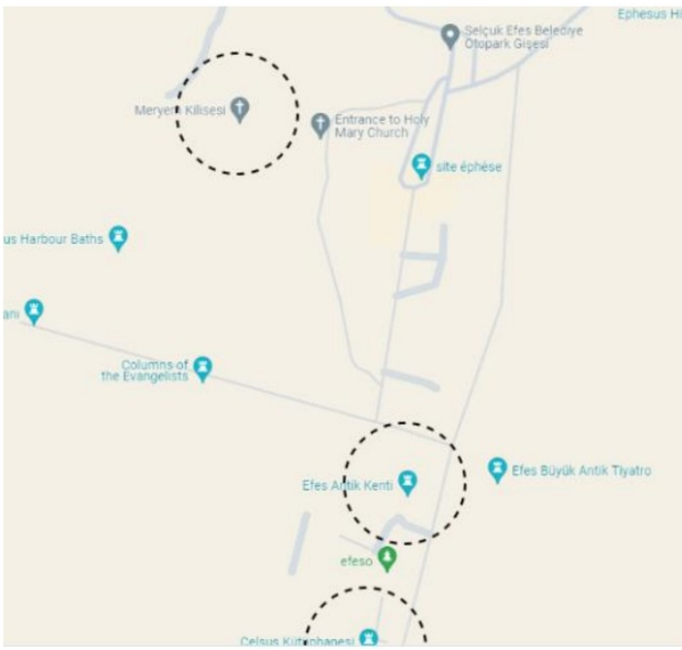

Figure 1 Geographical distribution of training locations: House of the Virgin Mary, Ephesus Ancient City, and Celsus Library.

For this purpose, artifact images were collected from each region, and the dataset was diversified to include various perspectives, lighting conditions, and environmental factors specific to each location. This localized data collection approach enables the model to learn distinctive features and contextual elements unique to each artifact. For instance, the House of the Virgin Mary, located in a wooded area, required the model to distinguish historical elements from the natural surroundings, while the Ephesus Ancient City, characterized by extensive ruins, presented challenges in separating structures from large-scale backgrounds.

The training process involved dividing the data into subsets corresponding to each region and applying model optimizations based on location-specific details within these subsets. This process was supported by data augmentation techniques, such as random rotation, brightness adjustments, and cropping, to simulate real-world variability. Additionally, cross-validation was performed on these subsets, ensuring the model's generalizability across all target regions while maintaining region-specific performance capabilities.

The location-based training strategy significantly improved detection accuracy, particularly in regions with visually complex or overlapping features. This result underscores the effectiveness of geographically tailored datasets in enhancing the capabilities of advanced object recognition algorithms.

Cross-Validation and Performance Evaluation

In this study, a 4-fold cross-validation method was employed to evaluate the performance of the YOLOv4, YOLOv7-X, and YOLOv9c models in historical artifact recognition tasks. The cross-validation approach enabled the assessment of the models' overall accuracy and generalizability by using each regional subset of the dataset alternately for both training and testing purposes.

The dataset was divided into four equal parts, with each part serving as the test set once, while the remaining three parts were used for training. During the cross-validation process, the following performance metrics were calculated for each model:

- **Accuracy**: The ratio of all correct predictions to the total number of predictions, expressed as:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{1}$$

  where:

  - TP: True Positives,
  - TN: True Negatives,
  - FP: False Positives,
  - FN: False Negatives.

- **Precision**: Measures how many of the predicted positive cases are actually correct, calculated as:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{2}$$

- **Recall**: Measures how many of the actual positive cases are correctly predicted, expressed as:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{3}$$

- **mAP (Mean Average Precision)**: Represents the mean of the Average Precision (AP) values across all object classes, calculated as:

$$\text{mAP} = \frac{1}{N} \sum_{i=1}^{N} \text{AP}_i \tag{4}$$

  where:

  - N: Total number of object classes,
  - AP_i: Average Precision for the i-th object class.

DATA COLLECTION AND PREPROCESSING

The data collection and preprocessing process used in this study was meticulously designed to ensure the robust and effective development of historical artifact recognition models. Images of cultural and historical artifacts were collected from three significant locations: **House of the Virgin Mary**, **Ephesus Ancient City**, and **Celsus Library**. These locations were selected for their architectural diversity and varying environmental conditions, providing a rich dataset for model training and evaluation.

Table 1 Comparative performance of YOLO models used for historical artifact recognition.

Model	Backbone	AP (%)	Key Advantages	Limitations
YOLOv4	CSPDarknet53	43.5	Robust feature extraction, scalable architecture	Limited suitability for lightweight applications
YOLOv7-X	E-ELAN	52.9	Improved efficiency, dynamic label assignment	More complex training process
YOLOv9c	GELAN and PGI	57.8	Superior gradient management, state-of-the-art accuracy	Higher computational requirements

Data Collection

At each location, photographs were captured under various lighting conditions and from different perspectives to enhance the diversity and generalizability of the dataset. A total of 762 images were collected, and the distribution of these images across the locations is presented in Table 2. These images captured fine details such as artifact textures, shapes, and environmental contexts, enabling the models to distinguish artifacts from their surroundings.

Table 2 Distribution of collected images across landmarks.

Landmark	Number of Images	Percentage (%)
House of the Virgin Mary	250	33
Ephesus Ancient City	320	42
Celsus Library	192	25
Total	762	100

Preprocessing Techniques

The collected images were subjected to various preprocessing steps to standardize and augment the dataset. Table 3 summarizes the key preprocessing techniques applied.

Table 3 Preprocessing techniques applied to the dataset.

Step	Description
Resizing	All images were resized to 640×640 pixels to match the input size requirements of YOLO models.
Data Augmentation	Random rotations, brightness and contrast adjustments, horizontal flips, and zooming were applied to simulate real-world scenarios and prevent overfitting.
CLAHE Enhancement	Contrast Limited Adaptive Histogram Equalization (CLAHE) was applied to enhance contrast in low-light or high-glare images, improving feature visibility.
Annotation	Artifacts in the images were manually labeled with bounding boxes following the YOLO format, compatible with YOLO training pipelines.

Dataset Splitting

The processed dataset was divided into three subsets for training, validation, and testing based on the locations. Initially, 15% of the total data from each location was allocated to the testing subset. From the remaining data, 25% was assigned to the validation subset, and the remaining 75% was used for training. This approach ensures that the models are trained and evaluated on geographically diverse subsets while maintaining proportional representation of each location in all phases of the process. Table 4 provides the detailed breakdown of the dataset split for each location. These data have also been augmented using data augmentation methods to increase fourfold.

Table 4 Location-based dataset splitting with test counts and adjusted validation/training.

Location	Subset	Images	Note
House of the Virgin Mary	Testing	38	Test set only
	Validation	53	25% of remaining
	Training	159	75% of remaining
Ephesus Ancient City	Testing	48	Test set only
	Validation	68	25% of remaining
	Training	204	75% of remaining
Celsus Library	Testing	29	Test set only
	Validation	41	25% of remaining
	Training	122	75% of remaining
Total		762	

EXPERIMENTS AND RESULTS

This section presents the experimental framework and results obtained during the evaluation of the YOLOv4, YOLOv7-X, and YOLOv9c models for historical artifact recognition. The experimental setup, including the hardware, software, and training parameters, is described in detail. The dataset preparation, which forms the basis of these experiments, is discussed in Section 'Experiments and Results'. The performance of each model is evaluated on the test dataset using metrics such as accuracy, precision, recall, and mAP. Additionally, the results are visualized through tables, charts, and example outputs, highlighting the models' strengths and limitations in real-world scenarios.

Experimental Setup

This section provides details on the hardware and software infrastructure used, the training parameters for each model, and a brief summary of the dataset utilized in this study.

Hardware and Software Infrastructure The experiments were conducted on a system equipped with an Intel Core i9-10920X CPU running at 3.50 GHz with 24 threads, 64 GiB of RAM, and two NVIDIA RTX A5000 GPUs, each with 24 GiB of VRAM. The system was running Ubuntu 20.04.6 LTS (64-bit) with NVIDIA Driver Version 535.216.01 and CUDA Version 12.2. For YOLOv4, the TensorFlow framework was used, while YOLOv7-X and YOLOv9c were implemented using the PyTorch framework.

Training Parameters Each model was trained using specific parameters tailored to its architecture and requirements:

- **YOLOv4:** The input image size was set to 416×416, with a batch size of 32. The model training utilized an initial learning rate of 0.001, following a step decay schedule for gradual reduction during training.
- **YOLOv7-X:** The input image size was 640×640, with a batch size of 32. The model was trained for 50 epochs, using the default learning rate settings.
- **YOLOv9c:** The input image size was 640×640, with a batch size of 32. The model was trained for 50 epochs, using the default learning rate settings.

Experimental Results

The performance of the YOLOv4, YOLOv7-X, and YOLOv9c models was evaluated on the test dataset using four key metrics: accuracy, precision, recall, and mean average precision (mAP). These metrics provided a comprehensive assessment of the models' ability to accurately detect and classify historical artifacts. The results are summarized in Tables 5, 6, 7, and 8, respectively.

The accuracy results, detailed in Table 5, highlight the differences in model performance. YOLOv4 achieved an average accuracy of 84% across the entire dataset, with location-based accuracies of 86%, 92%, and 94% for Celsus Library, House of the Virgin Mary, and Ephesus Ancient City, respectively, resulting in a location-based average of 91%. YOLOv7-X demonstrated an improvement with an overall accuracy of 85% and a location-based average of 95% (93%, 95%, 96%). Meanwhile, YOLOv9c outperformed both models, achieving an overall accuracy of 85% and a location-based accuracy of 96% (93%, 95%, 98%).

Precision, presented in Table 6, further distinguishes the models' performances. YOLOv4 achieved an overall precision of 81%, with location-based precision values of 87%, 88%, and 91% for the three locations. YOLOv7-X improved on these metrics with an overall precision of 83% and a location-based precision of 93% (91.0%, 93%, 97%). YOLOv9c, delivering the highest precision, achieved 84% overall and 93% location-based precision (92%, 94%, 94%).

The recall results, shown in Table 7, reveal similar trends. YOLOv4 achieved an overall recall of 84%, with location-based recall values of 90%, 86%, and 94%. YOLOv7-X improved these scores with an overall recall of 86% and location-based recall values of 94% (91%, 95%, 96%). YOLOv9c, once again, delivered the highest recall, achieving 86% overall and 95% location-based recall (92%, 95%, 97%).

Finally, mAP results are summarized in Table 8. YOLOv4 achieved an overall mAP of 66% and a location-based mAP of 68% (65%, 68%, 70%). YOLOv7-X improved these results with an overall mAP of 68% and a location-based mAP of 69% (68%, 69%, 71%). YOLOv9c, demonstrating the best performance, achieved an overall mAP of 70% and a location-based mAP of 71% (69%, 71%, 72%).

The results of the 4-fold cross-validation for the YOLOv9c model are presented in Table 9. Among the folds, Fold 3 achieved the best performance, with a recall of 95% and a precision of 93%. These values indicate the model's capability to accurately identify true positives and maintain high precision. Additionally, Fold 3 achieved accuracy and mAP values of 96% and 71%, respectively, demonstrating well-balanced overall performance. Based on these results, the model trained on Fold 3 was selected as the final model due to its superior metrics, which are critical for historical artifact recognition tasks.

To illustrate the real-world application of the developed system, Figure 2 demonstrates the interface of the artifact recognition application. The application first captures the artifact's image and determines its location. The corresponding YOLOv9c model is then applied based on the location, enabling the detection of the artifact. Once detected, the application provides detailed information about the artifact, including its historical significance and architectural details. In this example, the image of the Library of Celsus is processed, showcasing the system's capability to integrate artifact detection with user-friendly informational feedback.

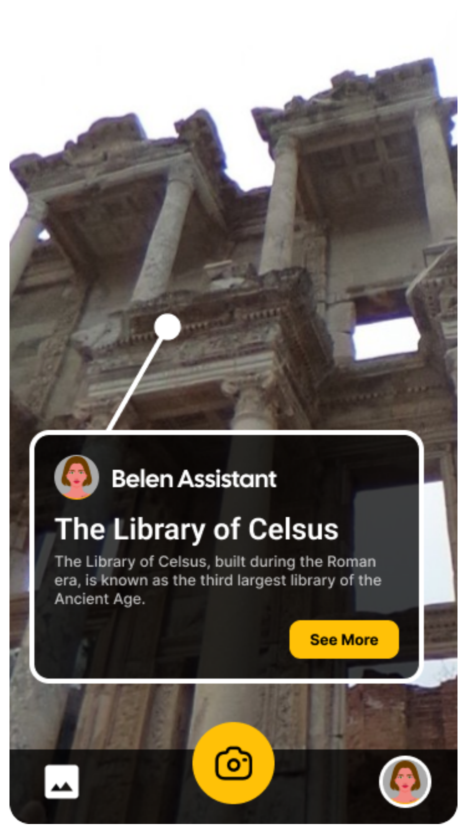

Figure 2 The interface of the artifact recognition application showing the Library of Celsus as an example output.

Table 5 Accuracy (%) results for each model across all datasets.

Model	Average	Celsus Library	House of Virgin Mary	Ephesus Ancient City
YOLOv4 (Overall)	84	-	-	-
YOLOv4 (Location-Based)	91	86	92	94
YOLOv7-X (Overall)	85	-	-	-
YOLOv7-X (Location-Based)	95	93	95	96
YOLOv9c (Overall)	85	-	-	-
YOLOv9c (Location-Based)	96	93	95	98

Table 6 Precision (%) results for each model across all datasets.

Model	Average	Celsus Library	House of Virgin Mary	Ephesus Ancient City
YOLOv4 (Overall)	82	-	-	-
YOLOv4 (Location-Based)	89	87	88	91
YOLOv7-X (Overall)	83	-	-	-
YOLOv7-X (Location-Based)	93	91	93	97
YOLOv9c (Overall)	84	-	-	-
YOLOv9c (Location-Based)	93	92	94	94

Table 7 Recall (%) results for each model across all datasets.

Model	Average	Celsus Library	House of Virgin Mary	Ephesus Ancient City
YOLOv4 (Overall)	84	-	-	-
YOLOv4 (Location-Based)	90	90	86	94
YOLOv7-X (Overall)	86	-	-	-
YOLOv7-X (Location-Based)	94	91	95	96
YOLOv9c (Overall)	86	-	-	-
YOLOv9c (Location-Based)	95	92	95	97

Table 8 mAP (%) results for each model across all datasets.

Model	Average	Celsus Library	House of Virgin Mary	Ephesus Ancient City
YOLOv4 (Overall)	66	-	-	-
YOLOv4 (Location-Based)	68	65	68	70
YOLOv7-X (Overall)	68	-	-	-
YOLOv7-X (Location-Based)	69	68	69	71
YOLOv9c (Overall)	70	-	-	-
YOLOv9c (Location-Based)	71	69	71	72

Table 9 Performance metrics for YOLOv9c using 4-fold cross-validation.

Fold	Accuracy (%)	Precision (%)	Recall (%)	mAP (%)
Fold 1	93	91	93	71
Fold 2	93	91	93	**72**
Fold 3	**96**	**93**	**95**	71
Fold 4	90	90	92	70

DISCUSSION

The experimental results revealed notable strengths and weaknesses of the YOLOv4, YOLOv7-X, and YOLOv9c models in the context of historical artifact recognition. Among the tested models, YOLOv9c consistently demonstrated superior performance, particularly in location-based evaluations, achieving higher accuracy, precision, recall, and mAP metrics. This highlights its ability to adapt to the complexities of diverse datasets and to effectively identify artifacts in varied settings. However, the computational cost of YOLOv9c, especially during training on high-resolution images, was significantly higher compared to YOLOv4 and YOLOv7-X. On the other hand, while YOLOv4 was computationally less expensive, its performance metrics, particularly for precision and recall, were inferior to the other models. YOLOv7-X provided a balance between computational efficiency and performance, making it a viable alternative for resource-constrained environments.

During the training process, several challenges were observed. Overfitting was a notable issue, particularly for the location-based models, as the dataset size was limited for certain locations. This was mitigated using data augmentation techniques, though further work is required to enhance generalization. Additionally, the computational costs of training larger models, such as YOLOv9c, posed significant challenges, especially on high-resolution datasets. For future work, improving model generalizability by incorporating more diverse training datasets and exploring lightweight versions of the models without compromising performance are recommended. Furthermore, integrating transfer learning and advanced optimization techniques could reduce training time and computational costs while maintaining high accuracy and robustness.

CONCLUSION

This study explored the performance of YOLOv4, YOLOv7-X, and YOLOv9c models for the task of historical artifact recognition, with a particular focus on location-based segmentation to improve detection accuracy. Among the models, YOLOv9c demonstrated the best overall performance, achieving the highest accuracy, precision, recall, and mAP metrics, especially in location-based evaluations. This highlights its robustness and adaptability to diverse and complex datasets, making it a suitable choice for applications requiring high precision and reliability.

Despite its superior performance, the computational cost of YOLOv9c remains a challenge, particularly for training on high-resolution datasets. Conversely, YOLOv4 was computationally efficient but lagged behind in terms of accuracy and precision, while YOLOv7-X offered a balanced alternative between performance and computational demands. These findings emphasize the trade-offs between computational efficiency and detection accuracy in choosing an appropriate model for specific applications.

The integration of location-based segmentation significantly enhanced the detection accuracy by enabling the models to specialize in recognizing artifacts within geographically defined contexts. This approach, combined with advanced cross-validation techniques, ensured robust evaluation and selection of the best-performing models. Additionally, the development of a user-friendly application interface demonstrates the practical utility of the proposed system in providing real-time artifact recognition and historical information to users.

Future work will focus on addressing the limitations observed in this study, including mitigating overfitting through more diverse and extensive datasets and optimizing model architectures to reduce computational costs. The integration of transfer learning, advanced optimization techniques, and lightweight model architectures will be further explored to improve efficiency without compromising performance. Overall, this research demonstrates the potential of deep learning models like YOLOv9c in enhancing the recognition and interpretation of cultural heritage artifacts, paving the way for innovative applications in heritage conservation and tourism.

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Availability of data and material

The data used in this study were sourced from specific cultural heritage sites and were subjected to preprocessing and data augmentation.

Conflicts of interest

The authors declare that there is no conflict of interest regarding the publication of this paper. Due to privacy concerns and the nature of the dataset, the data are not publicly available.

Ethical standard

The authors have no relevant financial or non-financial interests to disclose.

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