ESP-JETA
ESP Journal of Engineering & Technology Advancements
ISSN: 2583-2646 / Volume 5 Issue 4 October 2025 / Page No: 110-118
Paper Id: JETA-V5I4P117 / Doi: 10.56472/25832646/JETA-V5I4P117

Original Article

Data-Driven Optimization of Accounts Payable for Improved Financial Efficiency and Supplier Relations

Sandeep Gupta[1], Ruhul Quddus Majumder[2]
[1]*SATI, Vidisha*
[2]*Daffodil Institute of IT, Chattogram, Bangladesh*

Received Date: 13 September 2025 Revised Date: 09 October 2025 Accepted Date: 08 November 2025

***Abstract**: Effective accounts payable (AP) management is an important factor in operational excellence and financial stability in modern businesses. AP function, which simplifies cash flow and oversees supplier responsibilities, changed considerably depending on the changes of technologies and the dynamics of global supply chains. In this paper, the researcher examines how machine learning is applicable to automated invoice payment prediction to support the technique of effective financial processing in large-scale invoice distribution systems. The dataset employed in the research is of 100,000 transactions, where Decision Tree (DT) and Random Forest (RF) models are trained to recognize either paid or unpaid invoices. RF and DT had the highest accuracy of 90.66, 87.78 and F1-score of 93.34, 87.14, compared to the baseline models such as K-Nearest Neighbors (KNN) and Artificial Neural Network (ANN). Regular increases in the precision, recall, and F1-score are shown in all the results, which demonstrates the reliability of the models in relation to the real-world invoice automation. Overall, the study provides a scalable and data-oriented approach that would improve the financial decision-making process and make the automated invoice processing more productive.*

***Keywords**: Supplier Relationships, Financial System, Accounts Payable (AP), Supplier Relations, Transaction, Machine Learning.*

I. INTRODUCTION

The account payable (AP) is an important part of the finance of an organization. Good AP management helps in providing payments on time, maximizing the working capital, and enhancing the relationship with suppliers is enhanced [1]. The AP systems are the foundation of operational efficiency, enabling a smooth information flow between suppliers and customers. AP processes have the potential to lower costs, strengthen cash flow, and enhance the stability of the financial ecosystem of a company when managed well. Nevertheless, ineffectively handled AP may result in worsening of vendor relationships, loss of discounts and increased operating expenses [2][3]. Late or failure to pay on time not only spoils relations with suppliers, but it also has an impact on the reputation of an organization in the industry. These problems imply the necessity of a proactive approach to AP management, combining technological innovations with long-term planning [4].

In a fast-digitizing world, companies are under pressure to more modernize their AP operations. The suppliers demand speedy payments, increased transparency, and cooperation to regulate their cash flow effectively [5]. In the meantime, the organizations strive to create a balance between liquidity and preserving healthy relationships with the vendors [6][7]. The key to solving these conflicting needs in a particular way is the delicate knowledge of payment cycles, automation-based technologies, and supplier relationship dynamics [8]. Modern information systems are built on technologies such as artificial intelligence (AI), which liberates considerable potential in key supply chain decisions and operations. The interest in AI is growing among financial and technological providers to enhance the level of service and tailor their offers [9][10]. Businesses may more accurately forecast their cash flows, choose which suppliers to work with, and decide which solutions to pursue [11] with the assistance of AI. Machine learning provides it with an opportunity to work with big data sets, find latent trends and predict using past and current information [12]. Such abilities are especially applicable to the field of financial accounting, where the cost estimation and prediction is a multidimensional variable that are prone to unpredictable future. Various machine learning (ML) methods, include decision trees and regression analysis, more advanced models have been promising in solving these problems by providing more accurate and data-driven information.

A. Motivation and Contributions

The theory behind the research is that the importance of accounts payable (AP) as a source of sustaining organizational financial stability and supplier confidence cannot be overestimated. With the increasing rates of digitization and the necessity to pay the suppliers faster and more openly, the traditional AP processes usually fail to find the right combination between liquidity control and the contentment of the suppliers. The opportunity to modernize the work of APs with the help of modern technologies, including AI and ML, offers a potent chance to make all predictions and automate the workflow effectively and based on the data. With the help of these tools, organizations can save money, build stronger relationships with suppliers, and improve their financial stability in general, so there is no use denying the fact that intelligent AP management has become a strategic requirement in the contemporary competitive world. Here are some contributions summarized:

- Developed a complete invoice-payment prediction framework incorporating preprocessing, feature engineering, balancing, and classification.
- Applied Random Oversampling to address class imbalance, significantly improving minority-class detection accuracy.
- Engineered meaningful features such as Days to Due, contributing to stronger model interpretability and prediction quality.
- Integrated and evaluated Decision Tree and Random Forest models using a unified training and validation pipeline.
- To identify the best classifier, a thorough performance study was conducted using AUC, F1-score, recall, accuracy, and precision.

The originality of the current research is the utilization of an entire preprocessing-to-evaluation pipeline that has been specifically designed to predict invoice payments, which has few comprehensive machine learning studies. The combination of Min-Max scaling, derived time-based features (DaysToDue), and balanced training with the help of Random Oversampling results in a polished dataset, which substantially improves the model performance. The effectiveness of the suggested models is further justified by their better performance over the classical baselines (KNN and ANN), which shows that tree-based techniques are more efficient on heterogeneous invoice data. This tailored process demonstrates a practical and expandable approach to practical financial automation.

B. Paper Organization

The rest of this paper is structured as follows: Section II offers a literature review of the available literature on ML implementation in financial accounting, Section III presents the methodology of the research, which consists of a description of data collection, model choice, and metrics used to evaluate it, Section IV describes the empirical findings, and discusses them. Lastly, Section V Concludes important observations and recommendations on future research.

II. LITERATURE REVIEW

The literature review covers the emerging innovations on the use of AI and ML in finance, accounting, and processing invoices. The current study is based on the analysis, which shows that the results should be concentrated on the powerful and scalable models to enhance predictive accuracy in invoice processing.

Shaban and Omoush (2025) examine how Jordanian corporate governance and regulatory change are affected by AI-based financial transparency. The sample was also used to collect data on a stratified random basis of 564 corporate professionals in the major economic sectors. Statistical studies such as multiple regression analysis and structural equation modeling (SEM) show that the use of AI greatly increases stakeholder engagement ($R2 = 0.681$), risk management ($R2 = 0.502$), and corporate governance ($R2 = 0.582$). AI may also improve human errors in financial disclosures, automate monitoring chores, and assist with regulatory compliance. Nonetheless, there are still issues like AI-based algorithm bias, data privacy, and regulatory adjustments that are required. The results add to the literature of AI-enabled governance and offer insights regarding policy-makers and corporate executives [13].

Rahman and Zhu (2024) show that to identify accounting fraud, ensemble learning models outperform the method of logistic regression. Additionally, the imbalanced ensemble learning classifiers perform better than the traditional models. Importantly, the CUS Boost classifier is the only one of the discussed fraud classifiers that has shown the highest overall performance. The work is helpful for identifying accounting fraud in family companies because it shifts the paradigm of using traditional causal inference techniques (like regression) to ML-based prediction models. By tackling the problem of imbalanced data in fraud datasets and proving that unbalanced ML algorithms are more effective than traditional methods, it also advances the present corpus of research on accounting fraud detection [14].

Moore and van Vuuren (2024) suggest a generic structure of invoice payment prediction modelling with the goal of simplifying the process of preparing transaction data for analysis, generating characteristics from past customer behavior, and selecting and merging suitable models to forecast invoice payment times. Additionally, provide the Survival Boost algorithm, a novel sequential ensembling method. This strategy is supported by the notion that features generated by a survival analytic model can enhance the performance of an ML classification algorithm [15].

Kanaparthi (2023) built an artificial intelligence-based automated invoicing system using components. Invoices are processed entirely using this system. Configuring it to satisfy each individual customer's particular demands requires relatively little effort. The system is now being used in production by two clients. Approximately 80,000 invoices have been processed by it, 76% of them were processed automatically with little to no human involvement [16].

Heijden (2022) combines machine learning and publicly available financial statement information to forecast an organization's industry. The results show that an algorithm can use this data alone to properly forecast an industry sector, particularly when a non-linear classifier is used instead of a linear one. An industry-firm matching task from beginning accounting textbooks and MBA cases was also completed by the algorithms, and the predicted answers showed a high degree of accuracy. The study illustrates the potential use of ML techniques and algorithms in a number of accounting domains, where the main emphasis is on prediction rather than dependent variable explanation [17].

The prior research has shown that AI and machine learning can be useful in enhancing corporate governance, accounting fraud, and invoice processing. The majority of studies are done on a single industry or on rather small data sets, which restricts the applicability of the results. Not many studies adopt the problem of class imbalance in invoice or fraud datasets, which can bias the prediction of a model. Secondly, although they have proven to be effective, most ensemble as well as sequential learning methods have not been compared to classical methods like Decision Tree (DT) and Random Forest (RF) with regard to invoice payment prediction. The main contributions, datasets and limitations of these studies are summarized in Table I, pointing to the necessity to develop strong, scalable models that can work with large and lopsided datasets of invoices and provide predictive reliability and efficiency. The given gaps encourage the current study to examine optimized DT and RF models using a data balancing and feature selection method to predict the results of the invoices correctly.

Table 1 : Summary of Reviewed Studies on Accounts Payable for Financial Efficiency using ML

Author	Source	Methods	Key Findings	Contribution / Implications
Shaban & Omoush (2025)	Research on corporate governance, financial transparency, and regulatory change in Jordan using AI	Multiple regression analysis; structural equation modeling (SEM); stratified random sampling (n=564)	AI increases regulatory compliance, corporate governance (R^2=0.582), risk management (R^2=0.502), and stakeholder involvement (R^2=0.681); algorithmic bias and data privacy are obstacles	Provides empirical evidence for policymakers on how AI strengthens governance structures; highlights challenges requiring regulatory adaptation
Rahman & Zhu (2024)	Research on machine-learning fraud detection in family firms	Ensemble learning models; Logistic regression benchmark; CUSBoost and other imbalanced classifiers	Ensemble models outperform logistic regression; CUSBoost delivers the strongest fraud detection performance; imbalanced ML models improve detection in skewed fraud datasets	Shifts fraud detection research from traditional regression to predictive ML; emphasizes the importance of addressing data imbalance
Moore & van Vuuren (2024)	Framework for invoice payment prediction	Generic data-preparation and feature-engineering framework	Survival Boost enhances machine-learning classifier performance by integrating survival-analysis features	Introduces a hybrid ML-survival framework; provides practical guidance for predicting invoice payment timing
Kanaparthi (2023)	Implementation of an automated AI-based invoicing system	AI-driven invoice processing modules deployed in production	Processed ~80,000 invoices; 76% completed automatically with minimal human intervention	Demonstrates efficiency and scalability of automated invoicing; shows the feasibility of end-to-end AI invoice processing
Heijden (2022)	Machine learning for industry classification using financial statement data	ML classification (non-linear and linear models)	Non-linear models achieve high accuracy in predicting industry sectors; successful in textbook-style industry–firm matching	Demonstrates strong predictive power of ML in accounting; supports use of predictive analytics over explanatory models

III. METHODOLOGY

The research used a systematic approach that started with the collection of data using an invoice distribution system. It was pre-processed with the following features: converting the data to dates, encoding of labels, feature selection, Min-Max normalization and Random Oversampling to equalize the number of paid and not paid invoices. Two ML models, Random Forest and Decision Tree, were applied after the data was split into 70% training and 30% testing datasets. Accuracy, precision, recall, F1-score, and ROC-AUC were used to assess the model's performance and identify which classifier was best at predicting invoice status.

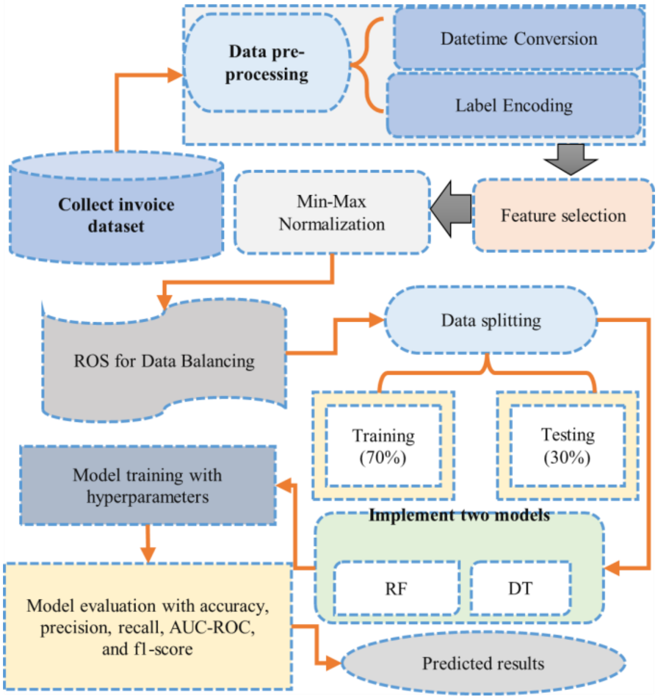

Figure 1 : Proposed Flowchart for Financial Efficiency and Supplier Relations

Each step of the proposed Figure 1 flowchart is briefly explained in the next section.

A. Data Gathering

The dataset of the invoice distribution company that was used in the study is 100,000 records with 12 attributes that contain data of the transactions and the customer. The entries have identifiers (Transaction Id, Invoice Number), channels of distribution (SMS, Print, Direct Debit, EInvoice), invoice amounts between 100.12 and 10,999.99 and temporal fields (Invoice Date, Due Date, Paid Date) (invoices that are not paid have a null).

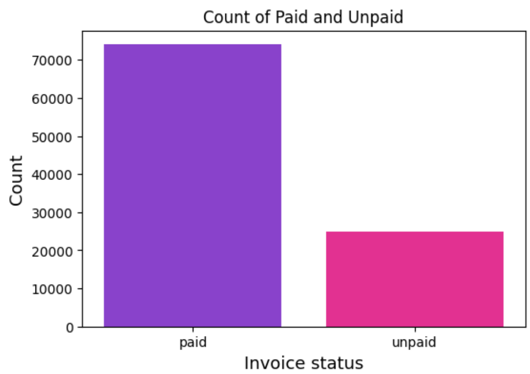

Figure 2 : Count Plot for Invoice Status Distribution

Figure 2 shows the distribution of invoice status, which provides a clear visual comparison between paid and unpaid invoices. The chart also shows a great imbalance, as the amount of paid invoices is much more than the amount of those unpaid. The tall purple bar represents the paid category, which occupies the major part of the dataset, whereas the unpaid category is represented by a shorter pink bar, which indicates the minority part. This asymmetric distribution highlights the necessity to incorporate data balancing approaches when training the model to avoid bias and guarantee equal classification performance between invoice statuses.

B. Data Pre-Processing

The procedures used to clean data and prepare it for usage in other contexts are referred to as data preparation. However, a series of steps must be taken to improve its quality before utilizing data in ML algorithms. The primary pre-processing methods are as follows:

- Datetime Conversion: The object types Due Date, Paid Date, and Invoice Date are now accessible. To aid with time-based computations, such as determining the amount of time needed to fulfill a deadline or pay an invoice, they were transformed to a DateTime format.

C. Label Encoding

In numeric columns, non-numeric values were assigned. For example, because there were only two categories, Distributed Channel, Gender, and Invoice Status were binary encoded. However, a label encoder was used to encode Distributed Channel because it had several categories.

D. Feature Selection

To select the features, the study selected the most relevant variables that were not redundant, and at the same time, multicollinearity was avoided. As both Age and Birth Year were available, then only Age was retained to represent demographic trends. The payment window was represented by a derived feature of DaysToDue, which was a calculation of the difference between Invoice Date and Due Date. Categorical attributes like Gender and Invoice Status were binary coded, whereas Distributed Channel was coded using labels owing to a number of categories. Finally, the features chosen to be used in training the Distributed Channel, Amount, Postal Code, Gender, Age, Invoice Status, and DaysToDue were among the models used to ensure that the data was condensed so that the machine learning predictions were accurate and effective.

E. Min-max Normalization

Data is standardized or scaled to a common range or format by normalization. Data normalization eliminates bias toward variables with larger values and helps to minimize numerical instability. In order to scale the characteristics to a range between 0 and 1, Min-Max normalizing methods were used in this investigation. The mathematical expression for normalization is Equation (1):

$$x' = \frac{x - \min(x)}{max(x) - \min(x)} \quad (1)$$

where x is the initial value, x' is the normalized value, $min\ (x)$ is the dataset's lowest value, and $max\ (x)$ is the feature's greatest value.

F. Data Balancing with Random Oversampling (ROS)

ROS is a practical and popular oversampling technique for addressing class imbalance. The ROS approach duplicates randomly selected minority class samples. Next, merge this new sample with the old data to train the machine learning models. By partially recreating the original minority dataset, this random oversampling strategy increases the probability of overfitting. Figure 3 represents the number count plot of invoice status following data balancing methods, which gives an almost equal representation of the two classes. Both classes are slightly over 25,000, which proves that the dataset has been balanced successfully.

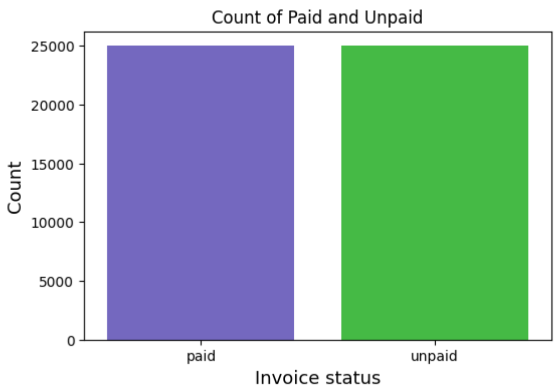

Figure 3 : Count Plot for Data Distribution After Balancing

Having this equal distribution makes sure that classification models are trained on balanced content and they therefore are better at generalizing and predicting the paid and unpaid invoice outcome more accurately without bias towards the majority class.

G. Data Splitting

The dataset was split into two halves as part of the experimental setup: 70% of the data utilized to train the models was in the training set, and 30% was in the testing set.

H. Propose Model

Two popular classification techniques—Random Forest, and Decision Tree are used to in this study.

a) Decision Tree (DT)

A decision tree is a kind of classifier where each hub or node represents a test on a dataset's attribute and its progeny represent the results [18]. Test data for node test information is subjected to a decision tree model. For every node in the tree, the optimal test condition or decision has P to be made. Equation (2), the optimal split is chosen using the GINI factor.

$$Gini(t) = 1 - \sum j \,[P(J|t)] \quad (2)$$

Where the relative frequency or general recurrence of class j at node t is denoted by $[P(J|t)]$.

b) Random Forest (RF)

Regression and classification problems may be resolved with Random Forest, a supervised ML approach. During training, it constructs many Decision Trees and uses a majority vote to determine the result, increasing Accuracy and yielding more accurate forecasts. The entropy and bootstrap aggregation criteria are used to improve precision.

$$IG(N_p, a) = Gini\ (N_p) - \sum_{i=1}^{c} \frac{|N_i|}{|N_p|} Gini\ (N_i) \quad (3)$$

$$Gini\ (N_p) = 1 - \sum_{j-1}^{m} p_j^2 \quad (4)$$

In Equations (3) and (4), $N_p$denotes the amount of data at the node N_p, and |Ni| denotes the amount of data at node Ni, where 0 ≤ I ≤ c. indicates that the amount of data having the jth label divided by the total amount of data at node N_p is the quantity of different labels of data at the node N_p. The label's number is indicated by the letter “j”.

I. Hyperparameter Training

In order to achieve optimal performance in predicting, the two models were trained using tuned hyperparameters found using grid search and cross-validation. In the case of the Decision Tree, the optimal environment was the Gini criterion, a maximum depth of 6, a minimum of 2 samples per leaf, and a minimum of four samples per split, which allowed for control overfitting and increased generalization. The best parameters of the Random Forest included n_estimators = 200, max depth =10, max features= sqrt, min sample split =3, min sample leaf=1, bootstrap= True. All these values contributed to the increased stability, decreased variance, and better ability to differentiate between paid and unpaid invoices.

J. Model Evaluation

The efficacy of a selected model was evaluated using a performance matrix that contrasted actual observations with model projections. The performance matrix included several variables, such as recall, accuracy, precision, and F1-score. The metrics listed below were calculated for different classes: True Negatives (TNs) were accurately classified as negative events, whereas A higher proportion of True Positives (TPs) suggests that positive cases were identified correctly. The following measures can represent the assessment metrics:

a) Accuracy:

Accuracy is the general performance based on how well the model classifies the outcomes giving a general evaluation of the performance. Equation (5) defines accuracy.

$$Accuracy = \frac{\mathrm{TP+TN}}{\mathrm{TP+Fp+TN+FN}} \quad (5)$$

b) Precision:

The following precision formula is used for determining the accuracy of positive forecasts. Equation (6) gives the precision formula.

$$Precision = \frac{\mathrm{TP}}{\mathrm{TP+FP}} \quad (6)$$

c) Sensitivity (Recall):

The percentage of positive samples that the model accurately identified. Equation (7) gives the sensitivity formula.

$$Recall = \frac{\mathrm{TP}}{TP+FN} \quad (7)$$

d) F1-Score:

To calculate the F1 score, a new value is computed from the precision and sensitivity. Equation (8) gives the F1-score formula.

$$F1 - Score = \frac{2(Precision * Recall)}{\mathrm{Precision+Recall}} \quad (8)$$

e) ROC-AUC:

ROC curve area under the curve that compares the False Positive Rate to the True Positive Rate (Recall). The total efficacy of the model is measured by the AUC.

$$AUC = \int_0^1 TPR(x)dx \qquad (9)$$

A greater AUC, as shown in Equation (9), denotes a model that performs better and can differentiate between classes more successfully.

IV. RESULTS AND DISCUSSION

A multi-core computer with the entire procedure made use of an NVIDIA GeForce GTX 980M graphics processing unit (GPU) with 8 GB of RAM, an Intel Core i7 CPU operating at 3.4 GHz, and additional components. The ML process was combined with Python 3.7. Table II shows that both models perform well on the invoice data set, and they have high scores in precision, recall, accuracy, and F1-score. The metrics of each of the measures can be viewed as indicators of the appropriateness of the model in appropriately labeling invoice results without a huge imbalance between relevant and misclassified cases. The scores are high and constant, which indicates that the proposed models are useful in the process of addressing invoice-related prediction problems and can be trusted to assist in automated invoice processing under realistic conditions.

Table 2 : Performance Evaluation of Proposed Models On Invoice Data

Matrix	DT	RF
Accuracy	87.78	90.66
Precision	88.34	92.68
Recall	89.25	91.57
F1-score	87.14	93.34

The Decision Tree (DT) model's confusion matrix, which displays the model's classification accuracy in predicting paid and unpaid bills, is displayed in Figure 4. This model accurately recognized 4,390 cases of paid (true negatives) and was misclassified 610 as unpaid (false positives). On unpaid invoices, it correctly predicted 4,460 cases (true positives) and falsely described 540 as paid (false negatives). These findings can be characterized as good predictive power, high precision and recall measures, and these values suggest the effectiveness of the DT model in the differentiation of invoice payment results.

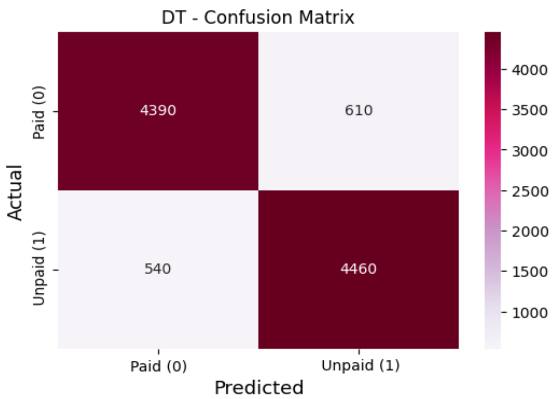

Figure 4 : Plot the Confusion Matrix of the DT model

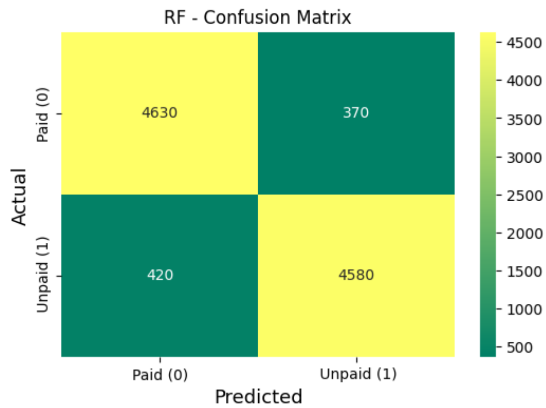

Figure 5 : Plot the Confusion Matrix of the RF model

Figure 5's confusion matrix demonstrates how effectively the RF model distinguishes between paid and outstanding bills. The model was accurate in forecasting 4,630 paid cases (true negatives), and it did not overclassify 370 cases as unpaid (false positives). On unpaid invoices, it had a hit rate of 4,580 (true positives) and a miss rate of 420 (false negatives). These outcomes depict a very high degree of accuracy and recall in contributing to the establishment of RF as the most suitable model in this research.

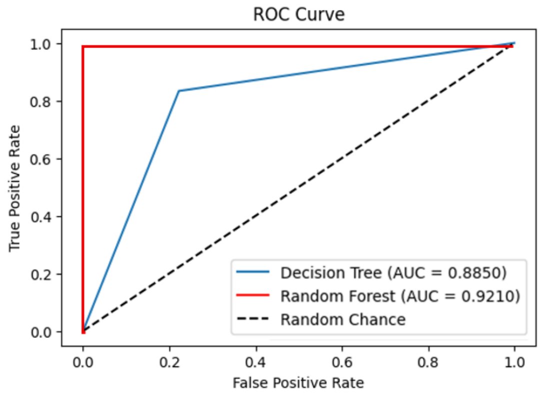

Figure 6 : ROC Curve Analysis of DT and RF Model

The comparison of the ROC curve between the DT and the RF models in Figure 6 depicts the potential that both models have to differentiate between the paid and the unpaid invoices. The RF model performs better, and its AUC is 0.9210, indicating that there is little class overlap and that the model is doing well. Conversely, the DT model has an AUC of 0.8850, which means strong yet marginally less strong discriminative power. The fact that the RF curve was more sensitive and specific, as evidenced by the fact that it was closer to the top-left corner, makes it a more useful model to predict invoice payments.

A. Comparison and Discussion

As demonstrated by the performance analysis, Table III demonstrates that both of the suggested models, in every metric, Random Forest (RF) and Decision Tree (DT) fared better than the fundamental models, KNN and ANN. The accuracy scores are 87.78% (DT) and 90.66% (RF), which is a sign of strong overall prediction. Additionally, the proposed models exhibit excellent precision, recall, and F1-score, with RF displaying the greatest values (Precision: 92.68, Recall: 91.57, F1-score: 93.34), indicating balanced performance in terms of minimizing incorrectly categorized instances and detecting relevant cases. The results denote the practical nature of the proposed models in the invoice data management and maximization of predictability rates to be utilized in the context of automated processing.

Table 3 : Comparison between base and proposed model performance

Evaluation matrix	Base		Propose	
	KNN[19]	ANN[20]	DT	RF
Accuracy	86.07	79	87.78	90.66
Precision	-	79	88.34	92.68
Recall	86.32	79	89.25	91.57
F1-score	85.45	79	87.14	93.34

The suggested Decision Tree and Random Forest models offer several advantages, including good recall, balanced categorization, and high accuracy in predicting invoice payment. They outperform the base models like KNN and ANN because they can also handle nonlinear associations, and they model significant characteristics besides resisting noise. On an individual basis, the random forest model has the greatest F1-score and AUC, making it the most stable and generalizable ensemble. These benefits underscore the importance of the proposed models in improving automated invoice processing, manual efforts, and the predictability of paid and unpaid invoices in a real-life financial setting with a high degree of reliability.

V. CONCLUSION AND FUTURE WORK

Automating the processing of incoming invoices might significantly improve accounting efficiency. This research has shown that ML models are effective in estimating invoice payment outcomes based on large real-life data. The quality of the data was enhanced by processing it systematically and thus providing more credible training of models. This research indicated that the suggested Decision Tree and Random Forest models are very efficient in predicting the outcome of invoice payment, with the best-performing model is Random Forest, which has a high degree of precision, accuracy, recall, and F1-score. RF model among all models provided better results with its accuracy of 90.66, F1-score of 93.34, DT had an accuracy of 87.78 and KNN and ANN had lower accuracy of 86.07 and 79, respectively, and this indicates that the model of ensemble learning offers better predictive potential to invoice classification. Nevertheless, the research also suffers due to the application of Random Oversampling which can result in overfitting and the limitation of the dataset to one company, lessening its overall applicability. There were only two ML models that were tested, and more sophisticated methods could be employed. Further research should be aimed at applying more powerful balancing techniques, including SMOTE or ADASYN, testing the models on multi-company platforms, and experimenting with modern algorithms, including XGBoost, Gradient Boosting, and Deep Learning. Moreover, the implementation of explainable AI can enhance transparency and make it easier to make better decisions regarding the automated processing of invoices.

VI. REFERENCES

[1] V. Prajapati, "Enhancing Supply Chain Resilience through Machine Learning- Based Predictive Analytics for Demand Forecasting," Int. J. Sci. Res. Comput. Sci. Eng. Inf. Technol., vol. 11, no. 3, pp. 345–354, 2025.

[2] K. Gao, X. Chen, X. Du, and K. Jiang, "Supplier concentration and corporate digitalisation: an empirical study using machine learning techniques," Int. J. Logist. Res. Appl., pp. 1–30, Nov. 2025, doi: 10.1080/13675567.2025.2584311.

[3] T. Shah, "The Role of Customer Data Platforms (CDPs) in Driving Hyper- Personalization in FinTech," Int. Res. J. Eng. Sci. Technol. Innov., vol. 12, no. 4, 2025.

[4] K. R. Kotte, "Accounts payable and supplier relationships: optimizing payment cycles to enhance vendor partnerships," Int. J. Adv. Eng. Res., vol. 24, no. VI, 2022.

[5] S. B. Shah, "Evaluating the Effectiveness of Machine Learning in Forecasting Financial Market Trends: A Fintech Perspective," in 2025 3rd International Conference on Integrated Circuits and Communication Systems (ICICACS), IEEE, Feb. 2025, pp. 1–6. doi: 10.1109/ICICACS65178.2025.10968297.

[6] A. Ronchini, M. Guida, A. Moretto, and F. Caniato, "The role of artificial intelligence in the supply chain finance innovation process," Oper. Manag. Res., vol. 17, no. 4, pp. 1213–1243, Dec. 2024, doi: 10.1007/s12063-024-00492-2.

[7] V. Varma, "Data Analytics for Predictive Maintenance for Business Intelligence for Operational Efficiency," Asian J. Comput. Sci. Eng., vol. 7, no. 4, pp. 1–9, 2022, doi: 10.22377/ajcse.v7i04.247.

[8] K. M. R. Seetharaman and S. Pandya, "Leveraging AI and IoT Technologies for Demand Forecasting in Modern Supply Chain," Int. J. Recent Technol. Sci. Manag., vol. 9, no. 6, 2024.

[9] H. Song, M. Li, and K. Yu, "Big data analytics in digital platforms: how do financial service providers customise supply chain finance?," Int. J. Oper. Prod. Manag., 2021, doi: 10.1108/IJOPM-07-2020-0485.

[10] S. R. Kurakula, "The Role of AI in Transforming Enterprise Systems Architecture for Financial Services Modernization," J. Comput. Sci. Technol. Stud., vol. 7, no. 4, pp. 181–186, May 2025, doi: 10.32996/jcsts.2025.7.4.21.

[11] A. Parupalli, "The Evolution of Financial Decision Support Systems: From BI Dashboards to Predictive Analytics," KOS J. Bus. Manag., vol. 1, no. 1, 2023.

[12] R. Dattangire, R. Vaidya, D. Biradar, and A. Joon, "Exploring the Tangible Impact of Artificial Intelligence and Machine Learning: Bridging the Gap between Hype and Reality," in 2024 1st International Conference on Advanced Computing and Emerging Technologies (ACET), IEEE, Aug. 2024, pp. 1–6. doi: 10.1109/ACET61898.2024.10730334.

[13] O. S. Shaban and A. Omoush, "AI-Driven Financial Transparency and Corporate Governance: Enhancing Accounting Practices with Evidence from Jordan," Sustainability, vol. 17, no. 9, 2025, doi: 10.3390/su17093818.

[14] M. J. Rahman and H. Zhu, "Detecting accounting fraud in family firms: Evidence from machine learning approaches," Adv. Account., 2024, doi: 10.1016/j.adiac.2023.100722.

[15] W. R. Moore and J. H. van Vuuren, "A framework for modelling customer invoice payment predictions," Mach. Learn. with Appl., vol. 17, Sep. 2024, doi: 10.1016/j.mlwa.2024.100578.

[16] V. K. Kanaparthi, "Examining the Plausible Applications of Artificial Intelligence & Machine Learning in Accounts Payable Improvement," FinTech, vol. 2, no. 3, pp. 461–474, Jul. 2023, doi: 10.3390/fintech2030026.

[17] H. van der Heijden, "Predicting industry sectors from financial statements: An illustration of machine learning in accounting research," Br. Account. Rev., vol. 54, no. 5, Sep. 2022, doi: 10.1016/j.bar.2022.101096.

[18] N. Prajapati, "The Role of Machine Learning in Big Data Analytics: Tools, Techniques, and Applications," ESP J. Eng. Technol. Adv., vol. 5, no. 2, 2025, doi: 10.56472/25832646/JETA-V5I2P103.

[19] T. Yuan, X. Zhang, and X. Chen, "Machine Learning based Enterprise Financial Audit Framework and High Risk Identification," Comput. Simul. Appl., vol. 3, no. 1, pp. 1–10, 2025, doi: 10.18063/csa.v3i1.918.

[20] İ. Dere, M. Turanlı, S. Alp, and M. Fındıkçı Erdoğan, "Analysis Impact of Financial Ratios on Bank Success Using Machine Learning Classification Algorithms: The Case of Turkey," J. Soft Comput. Decis. Anal., vol. 3, no. 1, pp. 50–71, Jan. 2025, doi: 10.31181/jscda31202553