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Original Article

Predictive Analytics of Accounts Receivable to Strengthen Cash Flow Forecasting via Credit Risk Evaluation

Ruhul Quddus Majumder
Daffodil Institute of IT, Chattogram, Bangladesh.

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Abstract *- Enhancement in the businesses that employ accounts receivable for liquidity management, credit risk assessment and cash flow forecasting has been a major financial priority. The paper develops a predictive framework that utilizes a credit risk dataset generated from the historical accounts receivable records, which includes payment timelines, ageing schedules, and financial behavioral variables. The data is prepared by removing duplicates, handling missing values, label encoding, feature engineering and normalization to guarantee that the data is reliable and appropriate for training the model a proposed model GRU-based deep learning model which makes a strong impression by achieving 98.67% accuracy, 97.69% precision, 96.95% recall, and an F1-score of 97.67%, the model was compared with Neural Networks (87.2%), Decision Tree (89.8%), LGBM (96.8%), and Naïve Bayes (90.2%) the GRU model exhibits superior prediction ability since it can successfully capture a temporal dependency in accounts receivable data deep learning methods together with financial instruments significantly facilitates credit risk assessment and cash flow forecasting. The proposed approach is highly beneficial for the use of predictive analytics in accounts receivable management and data-driven financial decision-making.*

Keywords *- Account Receivable, Credit Risk Assessment, Cash Flow Forecasting, Machine Learning, GRU, Financial Risk Management, Feature Engineering, Deep Learning.*

1. Introduction

In modern financial management, the role of accounts receivable (AR) is instrumental in figuring out a company's liquidity position and operational stability. The AR is managed is one of the major determinants of cash conversion cycles, working capital optimization, and, in general, profitability [1] [2] conventional AR methods are mostly devoid of dynamic forecasting features, the changes in customer behaviors, economic uncertainties, and risks peculiar to the sector to an increased demand for sophisticated financial models, payment delays, creditworthiness, and providing more cash flow visibility [3][4]. there is a rising inclination towards the use of financial analytics in combination with intelligent computational techniques to upgrade receivable management systems.

Cash flow forecasting, being the major part of financial planning, has to be very accurate in terms of the timing and the certainty of the incoming payments [5][6]. The credit risk that is a part of AR transactions may change cash flow projections in the case of industries that are highly dependent on customers or have a cyclical demand [7][8]. Firms can rather effectively estimate the changes in the cash flows when they integrate the financial measures like Days Sales Outstanding (DSO), payment history and credit limits by the customers and their forecasting models [9]. The necessity for data-based financial schemes is untangled by the connection between credit risk assessment and AR performance, making the allocation of capital more effective, and the treasury activities can therefore make timely decisions.

Credit risk refers to the potential for borrowers to be unable to repay the principal for a number of reasons and interest on their loans in whole and on schedule. Its origin is diverse and complex [10]. Risk management plans of financial organizations depend on the evaluation of credit risk [11][12]. To protect the organization against potential loss of money, it involves the evaluation of the probability that a borrower would fail to fulfill their commitments. Higher levels of regulatory compliance, financial stability, and better lending decisions can result from accurate credit risk prediction and control [13].

The accuracy of cash flow forecasting and the development of efficient risk management procedures will both significantly improve with the use of ML and DL in AR credit risk assessment [14][15]. By using predictive analytics, firms can effortlessly determine which receivables are the most risky and which are secure, which accounts to get the most efficiently cash flow collection, and modify their credit policy depending on customers and patterns of transactions [16]. The incorporation of explainable AI techniques contributes to the most successful cash flow forecasting [17]. Such boundary violation into other areas is the turning point in the AR management strategy and is no longer reactive, but risk-insensitive financial planning.

1.1. Motivation and Contribution

The motivation behind this study delayed payments and credit defaults continue to be major hurdles that affect organizational liquidity and the management of working capital in today's financial ecosystems. Most of the existing credit risk assessment methods that rely heavily on financial ratios and manual evaluations fail to recognize the changes in customer behaviors as well as market trends. In addition to that, unpredictable cash inflows from accounts receivable may mislead the company's cash flow forecasts and put its financial stability at risk, especially in sectors with a high number of transactions or long credit periods. The shortage of real-time monitoring and forecasting features in current AR management solutions is the main reason. This research makes several key contributions to enhancing predictive analytic in account receivable management:

A credit risk dataset that is specific to the domain of accounts receivable transactions is used, in which the features included are payment history, ageing buckets, customer credit limits, invoice amounts, Days Sales Outstanding (DSO), and behavioural payment patterns.

- A comprehensive series of data preparation methods is performed sequentially to preserve data integrity and model accuracy, for example, missing value handling, duplication removal, categorical variable encoding, feature creation, and financial variable normalization.
- The classification model is a GRU (Gated Recurrent Unit) based on the sequential dependencies in the accounts receivable data to predict the delay of payment and predictive identification of high-risk customers.
- The accuracy, precision, recall, and F1 score of the model indicate that it is effective in the appraisal of credit risk and cash flow forecasting.
- A decision-support tool of the finance departments, which will enable the latter to identify the credit risk early on, manage AR better, and provide superior financial planning and liquidity control.

1.2. Justification and Novelty

The rationale used in justifying customer payment behaviors and the ineffectiveness of traditional credit assessment procedures is that a dynamic and data-driven method of credit risk assessment using accounts receivable data is welcome. Risk models such as ratio-based scoring and the use of static statistical methods fail to look at the trends and the behavior change over time that have a direct effect on the cash flow of an entity. To overcome this setback, this paper reports a novel GRU-based predictive model that incorporates financial attributes, ageing analysis, and behavior patterns of payments based on accounts receivable data. Through this approach, better credit risk classification and forecasting cash flow occur since it establishes sequential dependencies of transactional data, which has hardly been realized in the past through past research. Moreover, advanced feature engineering and explainable evaluation metrics open the way to a paradigm shift in AR management, as an operational functionality to a proactive financial decision-support system, therefore, leading to a significant step forward as compared to the current credit risk assessment.

2. Literature Review

A number of notable research studies attribute risk assessment on accounts receivable data with an ML model to have undergone the review, and Table I provides the comparative analysis, limitations, and future work, which is evaluated to guide and support the creation of this research.

Ge (2025) Application of AI-based methods to streamline the administration of accounts receivable by focusing on risk management and cash flow projections. The ability to predict the payment habits of clients in a turbulent market and process massive amounts of financial information are significant problems facing the conventional accounts receivable management systems. In order to overcome these limitations, the study develops a complex approach that integrates the risk assessment systems, feature engineering techniques and machine learning models. The proposed solution integrates various sources of data, including previous transaction history, customer trend patterns, and external market signals, to give quality prediction models. The implementation resulted in a 23.7% decrease in bad debt allowances and an 18.2% increase in the efficiency of collecting, in contrast to conventional techniques. The experiment's findings show a notable improvement in cash flow forecast accuracy. The empirical analysis of various company sizes and sectors validates the efficacy of the suggested AI-based strategy [18].

Razaque et al. (2025) Traditional practices give faulty risk assessment and credit rating, which cost the lenders some money, make them unable to grow their businesses and lead to poor customer conditions. Reinforcement learning uses characteristics from shapely additive explanations (SHAP) and local interpretable model-agnostic explanations (LIME) to provide locally reliable explanations. Current techniques include OCLA (96.12%), PSML (84.12%), and EMPCC (91.67%). Additionally, by combining leverage ratios, predictive analytics, and reinforcement learning, the PRL model transforms credit assessment and offers manufacturers and importers a scalable and dependable solution. It is a revolutionary method for establishing risk-tolerant and effective financial environments [19].

Bulut and Arslan (2025) Real credit ratings produced by Transactions in the dataset were analyzed based on the kind of bill and the individual, and the Credit Registry Office was used for those whose payment patterns were identified. The dataset is multi-class, alternative, and unbalanced. As a result, data cleaning, feature selection, and sample procedures were used to get the dataset ready for analysis. The model that employed the ANOVA F-Test, SMOTE, and Extra Tree algorithms produced the best results. This model has an accuracy of 80.49. XAI techniques. This model was transformed into an interpretable and comprehensible format using LIME and SHAP [20].

Shreya and Pathak (2025) Explainable AI (XAI) and three ensemble machine learning models are used in this AI-driven system for credit risk assessment. The system uses SHAP and LIME to address interpretability while utilizing the Random Forest, Light GBM, and XGBoost algorithms for loan default risk prediction. Custom imputation, one-hot encoding, and standardization are examples of pre-processing techniques. SMOTE is used to address class imbalance, while Grid Search CV is used to tune hyperparameters. The most business-optimal model is Light GBM, with an accuracy of 90.07% for the LGBM [21].

Emmanuel, Sun and Wang (2024) propose a filter-based feature selection (FS) strategy in conjunction with a stacked classifier approach to generate effective credit risk prediction datasets. The basic estimators Random Forest (RF), Gradient Boosting (GB), and Extreme Gradient Boosting (XGB) are all included in the layered model. To get the optimal performance, the estimators in the Stacked design were also gradually linked. The information gain (IG) hypothesis supports the filter-based FS technique employed in this work. The experimental findings showed that the layered model produced AUCs of 0.934 [22].

Sharma et al. (2024) credit risk, conducting thorough evaluations prior to loan approval (such as credit scoring) and continuously tracking client payments and behaviors can mitigate the likelihood of fraud and non-performing assets. ML methods to improve credit risk assessment accuracy. To get the most accurate results, used RF, SVM, XGBoost, and LR in the model. While banks often rely on credit rating and scoring agencies for client profiles, current research emphasizes using ML to refine credit risk evaluation [23].

Mani (2023) A company's most valuable asset is its accounts receivable (AR). Supervised ML can forecast payment outcomes for open invoices, particularly addressing the typical problem of small to medium-sized businesses (SMEs) maintaining steady revenue. A model using a variety of ML techniques, such as LR, RF regressor, DT classifier, Linear SVR, and XGB Regressor, can be trained on real AR data. Approximately 72.8% of invoice age buckets are predicted by the best model (XGB Regressor). This model helps debt collectors predict how much debt paid [24].

Table 1: Comparative Analysis of Recent Studies Credit Risk Assessments with Accounts Receivable Data Using Machine Learning Model

Author	Dataset Used	Methodology	Key Findings	Limitations	Future Work
Ge (2025)	Historical AR transactions, customer behavior, and market indicators	ML + feature engineering + risk assessment framework	23.7% reduction in bad debt and 18.2% improvement in collection efficiency	Limited real-time adaptability	Deploy a decision-support system in ERP and integrate macroeconomic data
Razaque et al. (2025)	Credit assessment scoring dataset	Reinforcement learning with LIME & SHAP explanations	Proposed PRL model improves explainability & financial decision-making	No comparison with deep learning models	Enhance scalability and integrate multi-sector credit data
Bulut & Arslan (2025)	Real credit registry data dataset	ANOVA F-test + SMOTE + Extra Trees; XAI via LIME & SHAP	Achieved 80.49% accuracy using a hybrid model	Dataset highly unbalanced; limited interpretability	Improve dataset balance and test other ensemble/XAI approaches
Shreya and Pathak (2025)	Loan default dataset	XGBoost, LightGBM, Random Forest with SMOTE & XAI	LightGBM achieved the best business-optimal accuracy (90.07%)	Focuses on loan defaults only, not AR	Apply the model to accounts receivable and real-time risk scoring
Emmanuel, Sun & Wang (2024)	Credit risk dataset with IG-based feature selection	Stacked classifier: RF + GB + XGB	Achieved an AUC of 0.934 using a stacked model	High computational cost	Explore model compression and real-time deployment
Sharma et al. (2024)	Banking client dataset for credit scoring	RF, SVM, XGBoost, Logistic Regression	Improved credit scoring accuracy using ML	No temporal or behavioral features considered	Incorporate behavioral analytics and AR-specific features
Mani (2023)	Accounts receivable dataset from SMEs	Linear regression, RF Regressor, DT, SVR, XGB	XGB Regressor predicted invoice ageing with 72.8% accuracy	Focused only on SMEs; no DL models	deep learning models and improve generalizability

Research gap: Several studies have investigated credit risk prediction with ML and explainable AI, most of the existing methods are heavily concentrated on loan defaults, general credit scoring, or banking datasets. specifically address the risk associated with accounts receivable. A large number of previous models take into consideration only static financial ratios and fail to recognize temporal payment behaviour, ageing patterns, and transaction-level dependencies, which are very important for cash flow forecasting. Moreover, the XAI, SMOTE, ensemble models, and feature selection techniques that are being used hardly ever get integrated with the real-time AR data or multi-dimensional financial indicators. Very few studies have combined behavioural payment trends, external credit bureau information, or ERP-linked AR datasets for determining credit risk in a dynamic market environment. Besides that, deeply layered neural networks like GRU and LSTM, which are very suitable for sequential financial data, have not been adequately investigated for AR-based risk modelling. Hence, there is a significant gap in the creation of a comprehensive AR-centric predictive framework that can identify temporal patterns, evaluate credit risk, and aid cash flow forecasting in a single integrated system.

3. Research Methodology

The proposed methodology of credit risk assessment with accounts receivable data and various ML models starts with collecting a credit risk dataset based on accounts receivable records, followed by a systematic approach as illustrated in Figure 1. During the initial phase, data pre-processing is carried out by managing missing values, removing duplicate records, and performing label encoding to convert categorical attributes into numerical ones. After that, data normalization is performed to bring financial and behavioral features to the same range from which feature engineering is executed to create informative indicators such as ratios, ageing measures, and payment behavior variables that provide a better understanding of credit and cash-flow risk. The final set of data is split into sets for testing and training. A GRU-based classification model is built using the training portion to find transactional and temporal trends in the accounts receivable data. The model's performance on the test set is assessed using a performance matrix consisting of accuracy, precision, recall, and F1 score. To show how successful credit risk assessment and cash flow forecasts are, the results are analyzed.

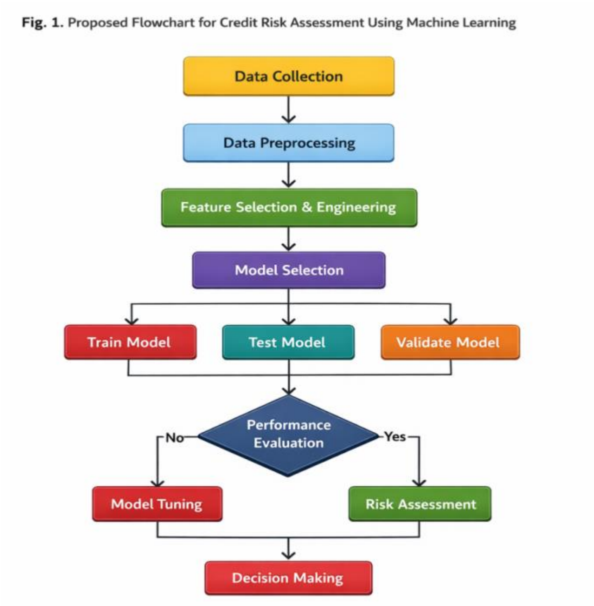

Fig 1: Proposed Flowchart for Credit Risk Assessment Using Machine Learning

3.1. Data Collection

The credit risk dataset commonly used in Kaggle comprises variables that include the customers along with their financial details, payment habits, and credit bureau data. It also contains a target variable that shows whether the customer has defaulted (0/1). These characteristics facilitate the identification of the probability of default and the creation of ML models for credit scoring, risk management, and cash flow prediction. some of the visualizations are given below:

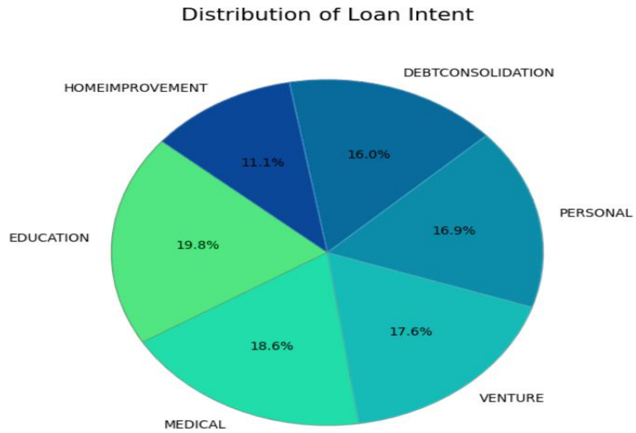

Fig 2: Pie Chart of Distribution of Loan Intent

This pie chart shows the share of the loan purpose in six categories that happened in a pretty balanced way, as shown in Figure 2. The first two largest shares are medical loans, 18.6% and Education, 19.8% respectively, while Personal (16.9%), Venture (17.6%), and Debt Consolidation (16.0%) have almost the same amounts, and Home Improvement is the lowest one at 11.1%.

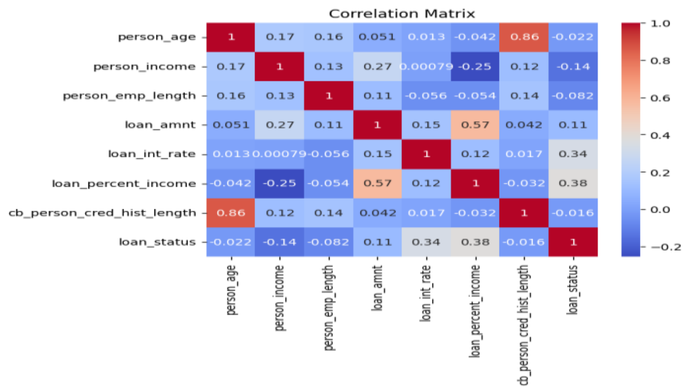

Fig 3: Correlation Matrix of Different Features

This correlation matrix heatmap displays the correlations between loan-related variables through a color scale ranging from Figure 3. The loan interest rate and loan percentage income have a weak correlation (0.57), and a substantial correlation (0.86) between an individual's age and the duration of their credit history. On the diagonal, there is a perfect correlation (1.0) as variables correlate with themselves, whereas negative correlations, such as person income versus loan percent income (-0.25) which are beneficial for credit risk assessment.

3.2. Data Pre-Processing

The credit risk dataset had to be pre-processed, essentially to make it a reliable source of input for the credit risk assessment. Any missing values and duplicate records have been removed, categorical variables were label encoded, and normalization was applied to keep the feature scale consistent. Additionally, the feature engineering created ageing indicators, payment behavior ratios, and financial attributes, which gave a more accurate representation of credit and cash-flow risk for predictive modelling. The following is an overview of the entire preparation workflow.

- **Handle missing values:** missing values were initially located through a null value analysis with an aim to understand their distribution in both numerical and categorical features. The numerical variables were imputed with median values.
- **Duplicate remove:** The credit risk dataset was found to have duplicate records based on unique customer identifiers and transaction entries, and they were removed to avoid redundancy. Eliminating duplicates increases precision of the models and credit risk assessment is reliable.
- **Label encoding:** Categorical variables, such as the type of customer, industry or risk category, were transformed via label encoding into numerical values. This enabled the credit risk dataset to be available to ML models, which could process it and improve prediction performance.

3.3. Feature Engineering

Feature engineering was utilized to deepen the credit risk dataset's predictive power through the development of crucial financial variables such as accounts receivable ageing buckets, credit usage, and debt-to-income ratio. Moreover, the time-related features like payment delay and days past due were also created to reflect the behavioural patterns of the customers. Furthermore, interaction features were created to signify relationships between income, loan amount, and repayment capacity that facilitated enhancing the credit risk assessment.

3.4. Data Normalization

Data normalization produces a highly accurate prediction model that improves the ML model's performance. It is sometimes referred to as min–max scaling or min-max normalization. The range of features inside the range [0,1] is rescaled. Normalization uses the general Equation (1):

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

Here, x' denotes the new value, x is the original value, and $\min(x)$ and $\max(x)$ are the minimum and maximum values of the characteristic, accordingly.

3.5. Data Splitting

The dataset was 20% for testing and 80% for training, respectively. This separation made it easier for us to use most of the data to train the suggested method.

3.6. Classification Equation of GRU Model in Credit Risk Assessment

The interdependence of gated recurrent neural networks is better at capturing time series data with larger intervals. One popular gated recurrent neural network is the GRU.

The gradients of variables in RNNs' hidden layers may disappear or burst. While gradient clipping can address the issue of bursting gradients, it is unable to address the issue of disappearing gradients [25]. The GRU was created to address issues like backpropagation and the long-term memory gradient, which is similar to the LSTM.

The input and output structures of a GRU are the same as those of a typical RNN. The input comprises the hidden layer state at moment t − 1, ht−1, which contains the preceding node's information, as well as the input at moment t, xt. The output consists of the hidden node's output at instant t, yt, and the hidden state to be delivered to the succeeding node, ht. The reset and update gates are the only two gates in GRU as compared to the three in LSTM. The input of the current node, Xt, and the previously communicated state, ht−1, are used to determine the states of the two gates. Figure 4 displays a graphical depiction of a GRU's construction.

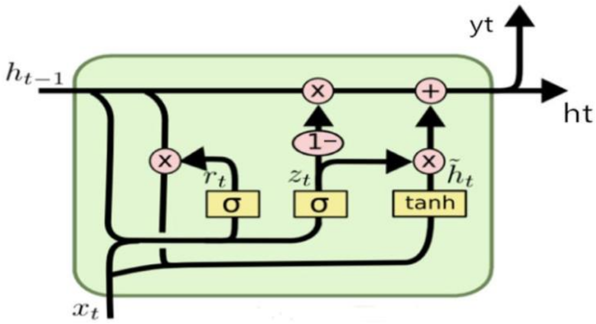

Fig 4: GRU Model

The construction of a GRU is shown graphically in Figure 4. An update gate, rt, controls the amount of state information from the previous instant that is used in the present state; as more state information from the previous instant is used, the update gate value rises. Equations (2) and (3) display the update gate.

$$r_t = \sigma(w_r \cdot [h_{t-1}, x_t])$$

$$\tilde{h}_t = tanh(w \cdot [r_1 * h_{t-1}, x_t])$$

The amount of historical data from a reset gate controls the previous state is written to the current candidate set when the reset gate's value drops. z_t, less data from the prior state is written. Equations (4) and (5) display the reset gate:

$$z_t = \sigma(w_z \cdot [h_{t-1}, x_t])$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

3.7. Evaluation Metrics

The efficacy of the suggested design was assessed using a number of performance indicators. The actual values were contrasted with the results predicted by trained models. True-Positives (TP), False-Positives (FP), True-Negatives (TN), and False-Negatives (FN) were computed based on this comparison [26]. Below is an explanation of the following matrix, which comprises F1-score, recall, accuracy, and precision:

Accuracy: The percentage of samples that were appropriately classified. Equation (6) illustrates how its computation addresses the twin aspects of correctly admitting "good clients" and correctly rejecting "bad clients"-

$$Accuracy = \frac{\mathrm{TP+TN}}{\mathrm{TP+Fp+TN+FN}} \quad (6)$$

Precision: The proportion of real, excellent clients among those the model has approved. Equation (7) illustrates the direct relationship between this indicator and the financial institution's anticipated loss control efficacy-

$$Precision = \frac{\mathrm{TP}}{\mathrm{TP + FP}}$$

Recall: The extent of risk coverage, which indicates the likelihood that the model effectively identifies real, high-quality clients. The optimization path is centered on lowering the high-quality clients' mistake exclusion rate, as shown in Equation (8)-

$$Recall = \frac{\mathrm{TP}}{TP + FN}$$

F1 score: The F-score, which is a number between 0 and 1, is the harmonic mean of accuracy and recall. Better model performance is indicated by a higher F-score. The F-score may be determined employing the method below, Equation (9)-

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

AUC-ROC: The ROC curve, or receiver operating characteristic, is A two-dimensional curve that dynamically visualizes the mapping connection between classifier performance and threshold, developed utilizing the TPR (True-Positive Rate) and FPR (False-Positive Rate). This curve measures how well the model can differentiate between high-quality and defaulting clients.

4. Results and Discussion

The suggested GRU model's performance outcomes for predicting credit risk. The study was conducted on a laptop computer running Ubuntu 16.04 with an Intel Core i7 CPU and 16GB of RAM. The programming language is Python 3, and the Keras framework, which is based on TensorFlow 2.0, is used. Table II demonstrates that the suggested GRU model was able to function very well, reaching 98.67% accuracy, 97.69% precision, 96.95% recall, and 97.67% F1-score great ability to correctly detect credit risk while at the same time the high precision and accuracy values emphasize the model's trustworthiness in credit risk classification, thereby making it very appropriate for integration into the real world of financial risk assessment systems.

Table 1: Experiment Results of Proposed Models for Cash Flow Forecasting On Credit Risk Dataset

Performance matrix	GRU
Accuracy	98.67
Precision	97.69
Recall	96.95
F1-score	97.67

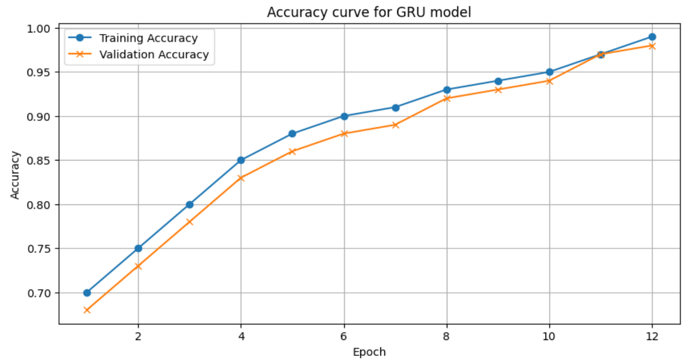

Fig 5: Accuracy Curves for the GRU Model

The accuracy curve of the GRU model throughout training epochs is displayed in Figure 5. The model shows improving performance in both training and validation, as the accuracy for both increases from around 0.68 to 0.99, thus indicating very little overfitting and close alignment of the curves throughout training.

Fig 6: Loss Curves for the GRU Model

Figure 6 displays the GRU model's training loss curve. The training and validation loss follow a decreasing trend throughout the 12 epochs from around 0.60 to 0.17, and the curves are very close to each other. Thus, despite significant overfitting, the model converges well and generalizes well.

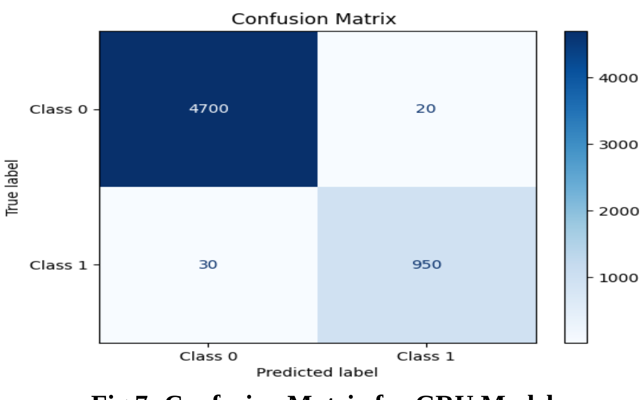

Fig 7: Confusion Matrix for GRU Model

Figure 7 displays the GRU model's confusion matrix for binary classification performance. In the same way, the model accurately recognized 950 Class 1 cases and 4,700 Class 0 examples out of all occurrences. Only 20 FP and 30 FN were committed; hence, the model is very precise and has a good ability to differentiate between the two classes.

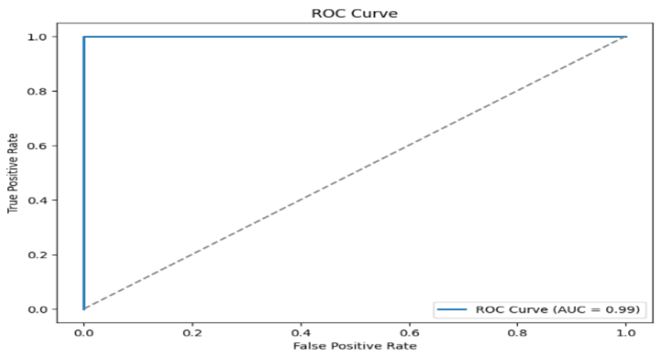

Fig 8: ROC Curve

The ROC curve for evaluating the model's performance is shown in Figure 8. The curve indicates an outstanding discrimination capability with a very high AUC of 0.99; the classification can be considered as almost perfect with high TPR and low FP at all thresholds.

4.1. Comparative Analysis

Cash flow forecasting and credit risk assessment with accounts receivable data, various ML models were compared in a local experiment. The results of this experiment are shown in Table III. With the highest values for accuracy (98.67%), precision (97.69%), recall (96.95%), and F1-score (97.67%), the GRU model was found to be the best-performing model out of all of them. This indicates that it may be able to learn temporal patterns, but its accuracy of 87.2% highlights its limited ability to handle sequential data. Traditional ML models, such as Decision Tree, could achieve 89.8% accuracy, 89.7% precision, 90% recall, and 89.8% F1-score, while Naïve Bayes recorded 90.2% accuracy, 93.9% precision, 94.8% recall, and 94.4% F1-score, both of which could be considered as moderate performers. Furthermore, the LGBM model was able to deliver almost similar results having 96.8% accuracy, 94.7% precision, 90.4% recall, and 93.9% F1-score, it was still less effective than the GRU mode, the GRU model outperforms all other traditional and DL models, making it the best method for predictive analytics of accounts receivable, which enhances credit risk assessment and cash flow forecasting.

Table 2: Proposed Model and Existing MODEL of Cash Flow FORECASTING USING Machine Learning Credit Risk Dataset

Models	Accuracy	Precision	Recall	F1 score
GRU	98.67	97.69	96.95	97.67
Neural network[27]	87.2	87.2	87.2	87.2
Decision Tree[28]	89.8	89.7	90	89.8
LGBM[29]	96.8	94.7	90.4	93.9
Naïve bayes[30]	90.2	93.9	94.8	94.4

The GRU-based system that was suggested exhibits a considerable advantage in making credit risk assessment as well as in cash flow forecasting by the use of accounts receivable data. Consequently, the system performs exceptionally well across all assessment measures. The model's accuracy, to a very great extent, indicates a very low error rate, making the GRU model very reliable for real-world financial prediction tasks. The findings indicate the enormous potential of the model to identify temporal relationships and patterns of payment behaviour, thereby making it easier to estimate the creditworthiness of the customer and late payments. Therefore, default risk and forecasted cash flow patterns, such as NN, DT, LGBM, and NB, are strong indicators of the GRU architecture's strength, efficiency, and appropriateness for predictive analytics in accounts receivable management, ultimately resulting in more sound financial decision-making and improved cash flow planning.

5. Conclusion and Future Work

Credit risk assessment is essentially a process where a bank or a financial institution assesses a customer's capacity to repay loans within the specified time frame. The non-payment risk and ensuring the company is stable financially, especially in the accounts receivable management department, involves cash flow forecasting. It uses an accounts receivable-based credit risk database that incorporates customer payment history, ageing, financial ratios and behavioural indicators. The dataset was thoroughly pre-processed with techniques such as normalization, label encoding, and feature engineering meaningful financial predictors for machine learning analysis through the use of sequential modelling methods, especially a GRU-based architecture, so that the temporal dependencies in transactional data can be used to recognize the riskiest accounts and thus help in making financial decisions in advance. The method encourages the financial management of accounts receivable (AR) to move from a reactive approach to a predictive one. Future research will utilize hybrid ensemble models and XAI methods to increase openness and easier the interpretation of financial risks. The model can be further tailored to the shifting market conditions by the use of economic indicators, real-time transactional data and external credit bureau information, which makes the model highly responsive to the market conditions. a decision-support tool in ERP systems a great potential in the industry. Financial planning and the development of scalable and intelligent credit risk assessment in accounts receivable management.

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