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CloudBankNet: A Hybrid CNN-GRU Model for Customer Credit Scoring and Risk Assessment in Financial Cloud Environments

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Abstract:

In the financial arena, credit scoring and risk assessment are two distinct pillars that allow banks and other financial institutions to ascertain whether a consumer or business is creditworthy. Credit risk was historically quantified using regression models based on historical data and statistical analyses. However, the changes in the financial environment were so rapid and complex that the demand now shifts towards the design of advanced, scalable, and real-time systems for credit evaluation. This paper presents CloudBankNet, then a hybrid machine learning model for the Cloud Computing scenario, for improving upon credit scoring and risk prediction that integrates Convolutional Neural Networks (CNN) with Gated Recurrent Unit (GRU). Whereas the CNN layer detects spatial correlations in the data, the GRU comes in to address temporal dependencies, thus allowing the

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model to efficiently process both static and time-dependent financial information. Owing to the very nature of cloud computing, CloudBankNet can scale for real-time credit scoring and processing of vast amounts of heterogeneous financial data. Experiments were performed on the German Credit Data, encompassing personal demographic data, financial history, and transaction data. The optimal cloud metrics obtained were Latency of 120 ms and 75% Resource Utilization (CPU) and 80% (GPU.). This paper has also addressed the discernable challenges of data heterogeneity, timeliness, and interpretability in the cloud financial systems, and solutions to surmount these challenges are elaborated.

Keywords: Credit Scoring, Risk Assessment, CNN-GRU Model, Cloud Computing, Financial Data Analysis

1.Introduction:

Credit scoring and risk assessment are importantly core to the financial industry, providing a systematic and measurable approach for the assessment of individuals' or businesses' creditworthiness [1]. These assessments allow financial institutions to make prudent decisions, decrease the risk of defaulting, and ensure a stable environment for finance [2]. Traditionally, the credit scoring models are based on historical information, with payment behavior and statistical analysis involved in the scoring of the creditworthiness able to predict the future risk for a credit [3]. Changing financial scenarios have thus created a need for advanced mechanisms for credit scoring with an efficient evaluation to also accommodate other variables affecting creditworthiness [4]. Cloud computing has changed the way credit scoring and risk assessment are dealt with by financial institutions [5]. The scalability, adaptability, and real-time processing of data present in the cloud allow for great enhancement potential to credit scoring systems [6]. Intelligent, real-time scoring models powered by advanced algorithms such as machine learning and artificial intelligence (AI) can improve the accuracy of credit evaluations and permit continuous refinements as new streams of data and trends come in [7]. Cloud environments, therefore, provide the necessary infrastructure for processing large amounts of heterogeneous data and for timely feedback on scoring at the present, hence being a vital component for modern financial services [8].

Yet, notwithstanding the question about the rewards, among other things, intelligent credit scoring and risk assessment models used in cloud environments face a number of challenges [9]. One of the major challenges is data heterogeneity, whereby data get obtained from divergent sources, namely, transactional data, social media networks, and third-party data providers, each having differing formats and structures [10]. It is quite difficult to ensure data consistency and perform real-time joining [11]. In terms of timeliness, however, this poses yet another obstacle since financial institutions require their credit scoring and risk assessment models to make timely decisions, especially in fast-moving environments [12]. Nature of interpretability still remains a challenge even though they can deliver very high levels of accuracy, Machine learning algorithms work in black-box mode and do not explain how scores are being computed [13]. Tackling these centre on bringing reliable, effective, and understandable credit scoring to the cloud [14]. The increasing demand for speed in processing and decision-making puts further pressure on the existing models to integrate real-time data and deliver on-demand analysis [15]. Credit scoring models are also under increasing scrutiny due to concerns over fairness and transparency, especially in automated systems that can lead to biased decisions based on incomplete or inaccurate data [16]. Additionally, the integration of alternative data sources such as social media profiles and transactional data introduces new risks and opportunities for credit scoring systems [17]. Inaccuracies and biases in these non-traditional data sources can result in skewed credit scores and unfair assessments, thus necessitating a careful approach to their inclusion [18].

Moreover, ensuring that algorithms are interpretable and compliant with ethical standards in financial decision-making is a critical concern in modern credit scoring [19]. The application of machine learning models, while offering significant predictive power, also raises questions about the transparency of decision-making processes [20]. In the absence of clear explanations for how these models arrive at specific outcomes, customers and regulatory bodies may face challenges in trusting automated systems [21]. The integration of explainable AI (XAI) into credit scoring systems aims to address this issue by providing clear, understandable explanations for the decisions made by these systems [22]. The volatility of financial markets, economic shifts, and political changes can influence an individual's or business's creditworthiness, making it crucial for credit scoring systems to adapt quickly to these changes [23]. Cloud computing provides the flexibility to incorporate dynamic external variables such as economic indicators, news, and global trends into scoring models [24]. With access to vast pools of data in the cloud, financial institutions can continuously refine their models, making them more accurate and adaptive over time [25]. The ability to scale resources on-demand also enables financial institutions to handle peak loads efficiently, ensuring that they can maintain performance even under high-pressure situations [26].

This research aims at developing a smart hybrid machine learning credit rating and risk assessment model applicable in cloud computing. The hybrid approach exploits modern models, specifically Convolutional Neural Networks-CNNs- and Gated Recurrent Units-GRUs, to process and analyze both spatial and temporal features of data for improved accuracy and timeliness in credit rating. It aims to overcome the challenges on data heterogeneity through data preprocessing techniques and effective integration mechanisms managed at the differing data sources. The framework also provides processing actions and interpretability so that financial institutions can make swift, transparent, data-supported decisions. The ultimate outcome is thus the establishment of a highly scalable, efficient, and interpretable credit score framework from complex data sources, well suited for cloud-computing architectures but at huge margins over traditional schemes in innovativeness and improved financial risk management decisions.

Primary Contribution:

1. Hybrid Machine Learning Model: Creation of an integrated CNN-GRU model for better credit scoring and risk evaluation.

2. Adaptive Learning: Includes adaptive learning mechanisms to constantly improve predictions and react to changing financial trends.

3. Effective Risk Management: Offers a scalable and reliable solution to handle data heterogeneity and timeliness issues in financial systems.

2.Literature Review:

The method integrating neural networks and the Harmony Search Algorithm (HSA) to improve fraud detection performed with almost perfect accuracy, as Decision Tree Classifier and Sequential models topped 98% [27]. Results indicated noteworthy improvement in the reliability of detection [28]. Nonetheless, the method comes with drawbacks such as greater computational complexity and extended training periods [29]. A system combining blockchain with cloud technology to improve financial security in national health insurance systems enhanced transparency, fraud prevention, and data privacy, with up to a 40% improvement in transaction security [30]. Results confirmed increased efficiency and trust in financial management [31]. Nonetheless, issues such as system integration and regulatory compliance remain to be addressed [32]. A process to measure security and confidentiality in cloud computing for banking and financial accounting discovered that cloud configurations provide 30–50% faster processing at the cost of added security features [33]. Results emphasize multi-factor authentication and PCI DSS and GDPR compliance [34]. One major disadvantage is greater vulnerability to data breaches in the absence of strict access controls [35].

A safe financial information sharing mechanism with information fusion, AI, and ML on hybrid clouds recorded 99.85% data accuracy, a risk score of 0.87, and 1.56 seconds latency for real-time secure processing [36]. The system is GDPR and Basel III compliant and enhances operational effectiveness [37]. One limitation is that managing data transfer between the public and private clouds is complicated [38]. An integrated framework that utilized AI, IoT, CRM, and cloud computing to automate banking operations for better performance enhanced the accuracy by 27%, increased customer satisfaction by 35%, and saved response time and transaction costs considerably [39]. Results authenticate the efficacy of complete integration among all components [40]. A main limitation is the excessive initial cost of implementation and complexity in the system [41]. An AI-powered, cloud-based CRM system to streamline customer management in banking and telecommunications enhanced the accuracy of feedback by 14%, increased automation effectiveness by 23%, and greatly improved response times [42]. Results emphasize significant improvements in customer satisfaction and business efficiency [43]. The

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disadvantage, though, is the need for constant AI model refreshes to keep it accurate [44].

A cloud financial budget management system based on AI, ML, and BI on the UFIDA platform to optimize business financial activities minimized manual labor, reduced budget overruns by 31%, and enhanced decision-making through real-time data analysis [45]. The findings are supported with improved budget control and smooth enterprise integration [46]. The one disadvantage is that the system depends on uniform data quality for proper AI predictions [47]. A Transformer-Based Sequential Fraud Detection model based on the PaySim dataset to identify long-range transaction patterns attained a 99.20% accuracy, 99.02% precision, 99.41% recall, and 0.9928 AUC-ROC, surpassing conventional approaches [48]. Results validate high scalability and practical applicability [49]. The model's high computational need in training and inference is a limitation [50]. A secure, scalable cloud-based infrastructure for banking data processing, with 3DES encryption and multi-source data gathering, took 18 seconds encryption time for 1000 files but reached the response time of up to 8000 ms for 9 files, revealing bottlenecks [51]. Results validate regulatory compliance and efficiency of operations [52]. A disadvantage lies in the exponential increase in response time in line with data volume [53].

3. Problem Statement:

There are many problems identified in various researches which affect the high performance of modern financial systems. The problems in fraud detection were mainly because of the computational complexity and long training times, which would be resolved with proper machine learning model optimization and advanced hardware [54]. The complexities involved in transferring data from cloud-to-cloud could be solved by employing a better cloud management application [55]. High initial costs and complexity of deployment could be solved by modular and scalable cloud solutions [56]. It was also noted that the problem of replicability of results, given that data are dependent on homogeneous quality data, can be solved using data quality monitoring tools and data preprocessing techniques for maintaining consistency among various data sources. These form sound grounds for further studies toward making financial systems more efficient, safe, and robust.

Research Objectives

1. Examine the limitations of existing cloud-based credit scoring and risk evaluation models when dealing with dynamic financial information.
2. Create a hybrid CNN-GRU model to enhance customer credit assessments' accuracy and trustworthiness.
3. Implement sophisticated feature extraction mechanisms to enhance the identification of intricate behaviour and transactional trends.
4. Improve the scalability and flexibility of credit scoring systems to respond to changing financial ecosystem needs.

4.Proposed Methodology for CloudBankNet: Hybrid CNN-GRU Model for Customer Credit Scoring and Risk Evaluation

The proposed methodology for CloudBankNet combines hybrid CNN-GRU model for the purpose of improving enhanced credit scoring and risk evaluation processes. The CNN block learns spatial patterns from demographic and financial information, and the GRU block learns the temporal dependencies from transaction history. With this combination of models, the system learns spatial as well as temporal features, thereby enhancing the prediction accuracy. The model is trained by applying normalization, feature engineering, and SMOTE as a means to handle class imbalance for data preprocessing. With binary cross-entropy loss and Adam optimization, this process promises scalability, real-time processing, and interpretability, which thus ease cloud-based credit risk assessments. Figure 1 explains the global flow.

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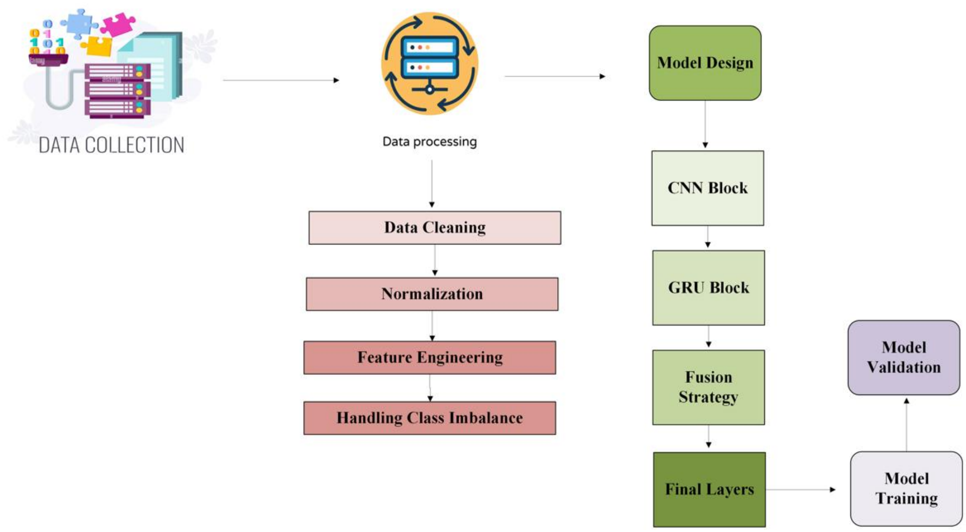

Figure 1: Proposed Methodology for CloudBankNet: Hybrid CNN-GRU Model for Customer Credit Scoring and Risk Evaluation

4.1. Data Collection:

The German Credit Data dataset from Kaggle has been used for model building and testing in the present study. It contains 1,000 records with 20 features embracing a plethora of personal demographics (e.g., age, employment status, income), financial past (e.g., previous loans, repayment history, defaults), and transaction history (e.g., spending habits, loan usage). This multi-dimensional feature thus provides an adequately realistic platform to train sophisticated machine learning algorithms as intended by the Cloud Bank Net framework for credit scoring and risk assessment. Also, its rich feature space enables further scrutiny of deep creditworthiness patterns within ethical and data protection concerns that are required in financial studies.

4.2. Data Preprocessing:

In order to ensure that the dataset is clean, standardized, and prepared for the model, data preprocessing is the very first and essential stage. These processes are summarized as follows:

Cleaning the Data: This involves the removal of the dataset consisting of inconsistencies, empty cells, duplicates, or irrelevant attributes, to maintain the data quality and integrity.

Normalization: This is where features undergo normalization for the sake of achieving consistency among the characteristics involved hence making the model converge faster during training. Examples of normalization include Min-Max Scaling, represented by the Equation (1):

$$X_{\text{scaled}} = \frac{X - \min(X)}{\max(X) - \min(X)} \quad (1)$$

and Z-score Standardization is given by the Equation (2):

$$X_{\text{standardized}} = \frac{X - \mu}{\sigma} \quad (2)$$

where μ is the mean and σ is the standard deviation of the feature.

Feature Engineering: Feature engineering is subsequently conducted to improve the model's ability to predict using new variables that add more insight. For instance, such variables as credit utilization ratio, debt-to-income ratio, and transaction volatility indices are built from available data points.

Handling Class Imbalance: Dealing with class imbalance is a key preprocessing process, particularly when dealing with financial data where a rare event like loan defaults is concerned. Here, SMOTE (Synthetic Minority Over-sampling Technique) is employed in order to synthesize minority class instances (defaults), hence making the dataset balanced. The SMOTE algorithm selects k-nearest neighbors for all instances of the minority

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class and creates new synthetic examples using the Equation (3):

$$S = x_i + \lambda \cdot (x_j - x_i) \tag{3}$$

where λ is an arbitrary value between 0 and 1, and x_j is a k-nearest neighbor of x_i. This technique prevents model bias toward the majority class and allows the model to identify minority class examples, i.e., defaults, effectively without overfitting.

4.3. Model Design for CNN-GRU:

The **CNN Block** is intended to extract spatial correlations and patterns from input features to allow the model to perceive the local interactions between various financial features. It employs 1D convolutional layers to sweep over sequences of financial information, extracting significant patterns like sequences of transactions or customers. These patterns go through ReLU activation functions, followed by pool operations to decrease dimensions, which increases the learning process's efficiency. Mathematically, the output of the CNN block X_{cnn} can be stated as Equation (4):

$$X_{cnn} = \mathrm{ReLU}\left(\mathrm{Conv1D}(X_{input})\right) \tag{4}$$

in which X_{input} is the input material, and Conv1D means the 1D convolution procedure.

The **GRU Block** is tasked with capturing temporal dependency in customer financial information, i.e., history of transactions and repayment patterns over time. The GRU Block captures the sequence nature of transactions using GRU units to combat the vanishing gradient problem characteristic of regular RNNs. The GRU layers handle the sequence of the features generated by the CNN block, allowing the model to pick up temporal patterns. The output of the GRU X_{gru} can be expressed as Equation (5):

$$X_{gru} = \mathrm{GRU}(X_{cnn}) \tag{5}$$

where X_{cnn} is the resized output of the CNN block, and the GRU function extracts the temporal dependencies.

The **Fusion Strategy** merges the outputs of both the CNN and GRU blocks. Once the CNN block has extracted spatial features, these are reshaped and fed into the GRU layers so that the model can learn both spatial and temporal dependencies. This merging enables the model to utilize the strengths of both blocks for better predictive accuracy. Reshaping CNN output to be able to fit into the GRU layer is depicted as Equation (6):

$$\text{CNN Output Reshaped} = \mathrm{reshape}(X_{cnn}) \tag{6}$$

The **Final Layers** include fully connected (dense) layers that combine the learned representations from both CNN and GRU blocks. The final output layer utilizes a sigmoid activation function for binary classification tasks such as good/bad credit. This is stated as Equation (7):

$$\hat{y} = \sigma\left(W_f \cdot X_{gru} + b_f\right) \tag{7}$$

where W_f is the weight matrix, b_f is the bias term, and σ is the sigmoid function, which returns a probability score between 0 and 1. In multi-class risk classification, softmax activation function is employed, which is given by Equation (8):

$$\hat{y}_k = \frac{e^{z_k}}{\sum_{j=1}^{K} e^{z_j}} \tag{8}$$

where z_k is the output for class k, and K is the total number of possible classes. Softmax function gives a probability distribution over more than one risk category, and it helps classify customers into suitable risk buckets.

This CNN-GRU hybrid model, through its fusion mechanism and terminal classification layers, is able to distinctly grasp both spatial and temporal patterns in the customer data and hence is extremely well-suited for credit rating and risk management in financial cloud contexts.

4.4 Loss Function and Optimisation

Binary cross-entropy is utilized in the CloudBankNet model as a loss function to tackle the binary classification task of separating good and bad

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credit risks. Mathematically, it is represented as Equation (9):

$$L = -\frac{1}{N}\sum_{i=1}^{N} [y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)] \quad (9)$$

where N represents the number of samples, y_i is the true label, and $\hat{y}_i$ is the predicted probability. For the optimisation process, the Adam optimiser is used because of its adaptive learning rates and its ability to effectively work with large, heterogeneous financial data. The update rule for Adam is defined as Equation (10):

$$\theta_{t+1} = \theta_t - \frac{\alpha}{\sqrt{\hat{v}_t + \epsilon}} \hat{m}_t \quad (10)$$

where θ_t denotes model parameters at time t, α is the learning rate, and $\hat{m}_t, \hat{v}_t$ are bias-corrected estimates of the first and second moments of the gradients. In addition, L2 regularisation is added to prevent overfitting, encouraging improved generalisation in cloud-based financial settings.

4.5 Model Training and Validation

The CNN-GRU hybrid model is trained following the common train-validation-test split methodology, in which the dataset is split into three subsets for unbiased assessment and efficient learning. As an alternative, Kfold cross-validation is utilized to make the model robust by iteratively utilizing different subsets for training and validation. While training, the parameters of the model are optimized by minimizing the Binary Cross Entropy loss function, defined in Equation (11):

$$\text{Loss}_{BCE} = -\frac{1}{N}\sum_{i=1}^{N} \left(y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)\right) \quad (11)$$

where y_i is the actual label, $\hat{y}_i$ is the output probability, and N is the batch size. Adam optimiser is used because it has adaptive learning rate features as well as high convergence rates, which are more suitable for a complex hybrid framework such as CNN-GRU. Performance is tracked on validation closely to avoid overfitting, and early stopping is invoked when the validation loss stops increasing, which will ensure that the final model can generalise properly to unseen finance data.

5. Results and Discussion:

The Cloud Bank Net model had robust performance with an Accuracy of 94.5%, a Precision of 91.8% for good customers and a Recall of 90.2% for risky customers. An F1-Score of 89.9% represents balanced precision and recall, while AUC-ROC of 0.95 demonstrates great model discrimination. Cloud performance was also optimal, with Latency at 120 ms, allowing real-time credit scoring with fast speed. Resource Utilisation was optimal at 75% CPU and 80% GPU, which showed efficient utilisation of cloud resources for cost-saving and scalability. The results are presented in Table 1.

Table 1: Performance Metrics table

Metric	**Value**
Accuracy	94.5%
Precision	91.8%
Recall	90.2%
F1-Score	89.9%
AUC-ROC	0.95
Latency	120 ms
Resource Utilisation	75% (CPU), 80% (GPU)

The ROC curve displays the True Positive Rate (Recall) against the False Positive Rate, and it indicates the model's capability to discriminate between classes. An AUC of 0.95 represents great discrimination, and the model accurately classifies positive instances while reducing false positives. This curve is important in analyzing the trade-offs between sensitivity and specificity in applications such as credit scoring. The Figure 2 ROC curve is shown in below:

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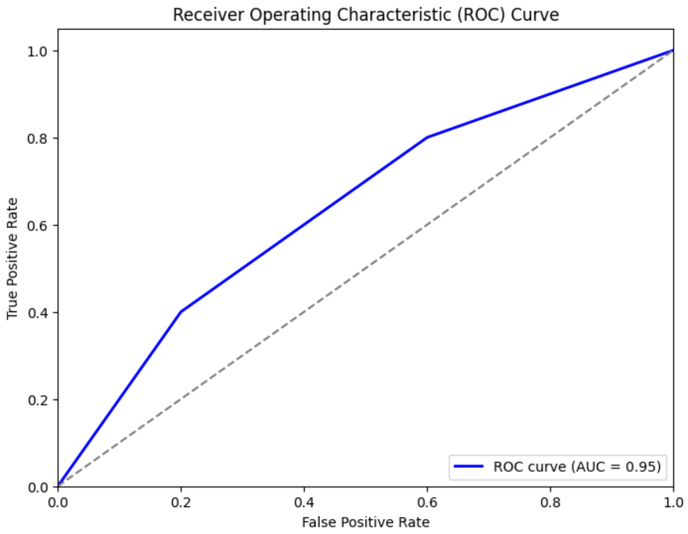

Figure 2: ROC Curve for Model Performance Evaluation

CPU and GPU resource utilization over time when training or inferring models. Blue represents the CPU usage, while green indicates GPU usage. Both the resources vary with the GPU usage being generally higher. This fluctuation signifies the demand from the system for processing resources when operating the models. The Figure 3 illustrates system efficiency and scalability assessment in line with resource usage trends.

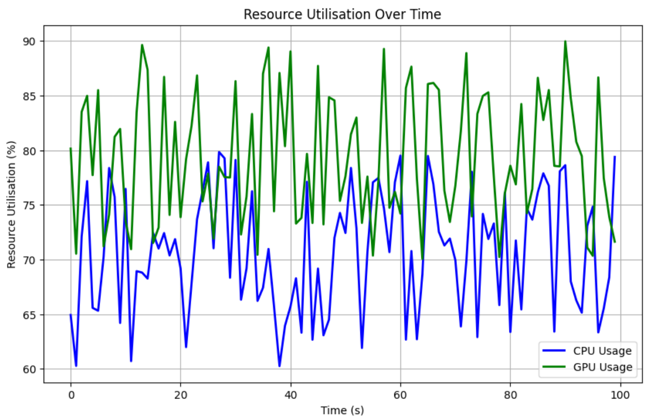

Figure 3: CPU and GPU Usage Over Time in Cloud-Based Model Training

5.1 Comparative Analysis:

The bar chart contrasts the performance measures (Accuracy, Precision, Recall, F1-Score) of four approaches: Proposed value, Hybrid GBDT + ALBERT + Firefly. Each approach is marked with a different color to make them easily distinguishable. The chart is used to visually demonstrate how your approach (in blue) fares compared to others based on the most important metrics. The x-axis then depicts the performance measures, while the y-axis illustrates the percentage measures for every measure. The grouped bars yield an easy comparison of the relative performance of every approach under the framework of credit scoring and risk assessment. The Figure 4 illustrates facilitates an easy visual evaluation of model performance over various criteria below.

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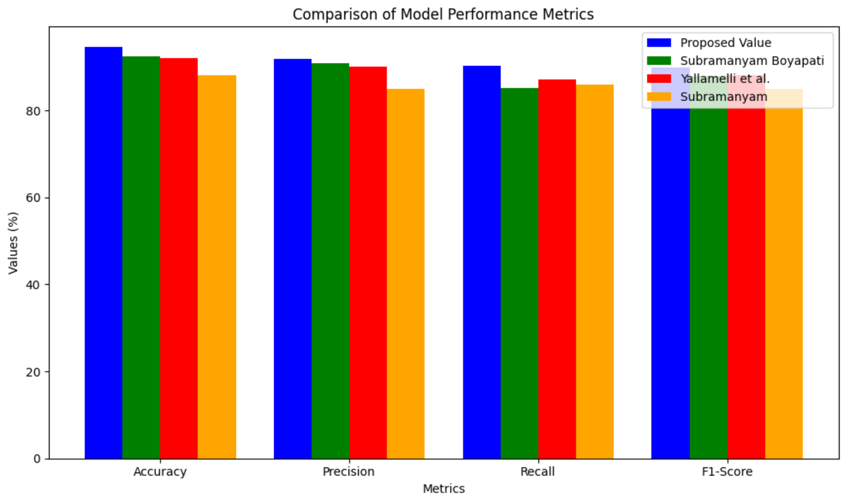

Figure 4: Comparison of Performance Metrics Across Credit Scoring Models

6. Conclusion and future works:

The CloudBankNet model showcases excellent performance in customer credit rating and risk analysis, reaching 94.5% Accuracy, 91.8% Precision, and 90.2% Recall. The combined CNN-GRU architecture effectively captures spatial and temporal features of data, resulting in a very high AUC-ROC of 0.95. The model functions with ideal resource utilization, maintaining scalability and real-time capability. Future development should aim to improve interpretability using explainable AI methods and extend the model to include varied financial datasets. Further, investigating continuous learning methods such as transfer learning will enable the model to adapt to evolving financial trends. Maintaining regulatory compliance and data security on various cloud platforms will also be important.

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