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FinTech Innovations: Cloud-Enabled Financial Services for Scalable Digital Banking

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Abstract

Over the past few years, Financial Technology (FinTech) has revolutionized the financial services sector by improving the efficiency, automation, and scalability of loan approval systems. The financial sector moves increasingly towards automated decision-making, robust and scalable loan approval prediction systems become imperative. This work aims to propose and assess a cloud loan approval prediction system based on a Feedforward Neural Network (FNN) that enhances the prediction accuracy and scalability. Comprehensive data preprocessing techniques are integrated into the proposed methodology, involving missing value handling through imputation, scaling and normalization, and label encoding for categorical variables. This makes the data available for modelling, reducing bias and improving model accuracy. The FNN model is hosted and trained on Amazon Web Services (AWS) cloud infrastructure to allow the system to scale efficiently and process big data effectively while maintaining computational performance. The model attained exceptional performance, with precision, recall, accuracy, and F1-score of 0.9996, 0.9997, 0.9996, and 0.9996, reflecting its high accuracy in both loan approval and rejection predictions. The results strength is giving reliable real-time loan predictions, while the cloud infrastructure provides low latency and guarantees scalability for big financial applications. This research shows how cloud-based machine learning (ML) can make a considerable difference in loan approval processes by boosting automation and efficiency, providing a reliable solution for changing financial scenarios.

Keywords: Financial Technology, Cloud-enabled Services, Digital Banking, Feedforward Neural Network, Loan Approval

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1. Introduction

FinTech has transformed the financial services sector and made the industry more effective, cost-efficient, and presented ground-breaking solutions to its customers [1]. Cloud-enabled digital banking has emerged to be one of these innovations and is now a source of scalable financial services and a perfect implementation of modern technology within financial systems [2]. With the transition to digital transformation among financial institutions, necessity to have strong and automated systems to analyses loan application has become very high and as a result, more accurate, scalable and efficient ways of predicting the loan approval have been required [3]. Cloud technology can transform the way banking is conducted in the past with its capacity of utilizing large amounts of data and complicated models [4].

Some of the factors affecting the approval of a loan are the credit score, income, the amount of the loan and the history of the loan repayment of the applicant [5]. Economic conditions and bank policies are other external factors that are also significant in deciding whether a loan will be approved [6].

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The conventional loan assessment processes, which tend to be subjective and rely on fixed rules, are growing obsolete in a world where digital solutions are able to handle high volumes of information in a short period of time and with precision [7]. All this creates the necessity of more automated and accurate loan approval systems using ML and artificial intelligence (AI) to forecast the results based on historical data [8].

Numerous existing approaches have been suggested to predict loan approval based on automation of procedure, such as Logistic Regression (LR), Support Vector Machines (SVM), Decision Trees (DT), and Random Forest (RF) [9]. The approaches have been successful in dissimilar measures, and each approach has distinct advantages. An example of this is LR which is often applied in binary classification problems such as loan approval because it is easy to interpret and use [10]. Non-linear relationships may however not work with it. SVM are great with high-dimensional data only that their performance may deteriorate with big data or data with noise [11]. DT are simple to interpret, but they might overfit the data, whereas RF tries to reduce overfitting through the use of multiple DT, which can also be a computationally-intensive way. Although the methods have advantages, they have weaknesses in respect of scalability, interpretability, and accuracy with complex and large-scale financial data [12].

The framework will address the limitations of the current approaches to using cloud-powered FinTech services and an FNN to classify the loan approval. The novelty of the given study is the adoption of the cloud infrastructure to manage data processing and model deployment on a large scale, to provide scalability and real-time predictions. Also, predictive performance in the FNN model is better because it relates complex and non-linear relationships among loan characteristics, which the traditional approaches can fail to capture. Deep learning algorithms allow to automatically gain experience in interactions between features, which offers a more efficient time solution to loan prediction problems. This method also enhances the efficiency and adaptability of the system through the use of the cloud-based tools to model training and deployment, as it is appropriate in a dynamic financial environment. The traditional methods of loan approvals which concentrate more on using only machine learning algorithms, this paper explores the development of Feed Forward Neural Network (FNN) which uses cloud technology for improving both data preprocessing and cloud deployment. The uniqueness of this work is the fusion of deep learning and cloud computing in order to achieve loan predictions at high accuracy levels through real-time predictions. Another unique aspect is the implementation of effective data preprocessing procedures. The key contribution of this paper:

- Created a cloud-based loan prediction interface based on FNN to improve the scalability and efficacy of digital banking, namely, real-time loan approvals predictions.
- Implemented advanced data preprocessing techniques, including handling missing data, normalization, and label encoding, ensuring high-quality data input for the FNN model.
- Leveraged the BigQuery FinTech Dataset to train and test; this made sure that complete and representative data is available to predict loan outcomes based on the key features, including credit score the loans and income.
- Enhanced scalability and prediction possibilities, through the deployment on cloud infrastructure, able to handle large-scale data efficiently and fast decision-making in dynamic financial environments.

The organization of this paper follows: Section 2 will contain a literature review, Section 3 will explain proposed methodology of loan approval prediction, Section 4 discuss on results, and conclusion of paper will summarize findings and provide directions for future research.

2. Literature Survey

Financial inclusion and digital technology, possibility of innovations such as cloud-based core banking systems contributing to possibility of financial access is promoted. Nevertheless, generalizing such technologies is not an examined process. The importance of market formation in digital innovation adoption is highlighted in research and topic of balance between laissez-faire and dirigiste mechanisms is relevant. Although less intervention by central banks can lead to diffusion of digital technology, greater action is essential in ensuring that wider objectives in society, such as financial inclusion, are realized faster [13]. The banking performance during digital era is highlighted in literature with a focus on necessity to modify conventional means of evaluation to consider new technologies such as FinTech and blockchain. Research indicates that multi-criteria decision-making, like Data Envelopment Analysis (DEA), is important in evaluation of operational efficiency. Digital metrics, including mobile banking and blockchain use, have become essential in explaining changing dynamics of work of banks, particularly in new economies that are in process of digital transformation [14].

FinTech adoption literature points out transformative intentions it has shown in financial industry especially with regards to efficiency, convenience, and security. Research studies factors that affect its adoption and organizational factors. Emphasis is also given to environmental and consumer trend as a factor causing adoption particularly among SMEs. The effects of external forces, including international crises like the COVID-19 pandemic, are usually taken into account when developing adoption intentions [15]. The changing threats to financial stability and consumer protection are discussed on emerging risks in digital banking context, which is operated by fintech. Geographical and disciplinary dynamics in fintech research are pointed out by comparative bibliometric analyses, particularly in such countries as China and India. This literature highlights the necessity of an effective risk management construct to help deal with complex effects of fintech on banking industry [16].

The FinTech adoption literature examines the drivers of adoption, perceived benefits and risks, and how other external factors such as COVID-19 pandemic affect adoption. Research also looks at how consumer attitude like fear can influence adoption decision. Moreover, the studies indicate the connection between the adoption of FinTech and sustainability and how it may impact the economic, environmental, and social performance. Such theories as the net valence framework and the protection motivation theory were used to comprehend these dynamics [17]. The reviews of AI adoption in the FinTech sector demonstrate that it has a transformative effect on the operating processes, development of products, and risk mitigation, which affect the company valuation. Research highlights the importance of AI in developing inter-relational models of real time adjustments and predictive features. Another field of research is the necessity of a balanced application of AI in different fields, responding to such risks as algorithm bias and regulatory problems and prioritizing value creation. All of this is essential to FinTechs, investors, and regulators [18].

Sustainable finance and fintech solutions in emerging markets have been addressed in potential of technology to promote financial inclusivity and sustainability. Research points to the potential of fintech in improving access to financial services to both underbanked individuals and SMEs and responsible consumption objectives by offering improved payment systems. Moreover, it has been indicated that fintech, specifically, Big Data, AI, and blockchain, can be used in mitigating finances against climate-related risks and enhance sustainable finance strategies in new economies, such as Turkey [19]. FinTech adoption literature discusses determinants of consumer adoption support as well as addresses obstacles such as lack of literacy and perceived risk. Effects of FinTech adoption on traditional banks are focus of research, with both positive results, including more efficiency and customer loyalty, and some challenges, including compliance charges. The major models that are applied in studies are Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT), which connect the behavioral and organizational approaches [20].

According to the literature on FinTech development in the ASEAN-4 countries, economic and technological issues are important to promote financial inclusion and availability of digital services. Although former researchers are focused on economic factor, there is a lack of research on special circumstances that shaped FinTech evolution in developing ASEAN markets. The studies highlight that financial access, technological preparedness, and macroeconomic factors contribute to development of FinTech. This research requires better digital infrastructure and economic accessibility to develop a sustainable and resilient FinTech ecosystem in the emerging economies [21]. There is also convergence of elements of environmental sustainability and financial innovation in green finance and FinTech literature, especially under Sustainable Development Goals and Global Compact principles of UN. Although studies in these areas have advanced, they have not yet merged to any significant degree between the green finance and FinTech areas. Additional research has been suggested by studies to be necessary on investment characteristics of green finance, FinTech solutions, regulatory issues in emerging economies, and new direction of Green FinTech [22].

The FinTech literature on blockchain-based FinTech emphasizes the revolutionary nature of the blockchain technology in improving trust and removing the third-party verification aspect in financial services. Research is in the field of integrating technologies in FinTech, where blockchain is central to overcoming the challenges in operations. Studies also look at different applications of blockchain, its use in the FinTech industry, and constraints and challenges of FinTech businesses migrating to blockchain and distributed ledger technologies [23]. The sources concerning FinTech and AI in sustainable development reveal their functions to support the green agenda and social responsibility. Research examines how FinTech can make financing economic and social projects easier, and AI can improve the decision-making process that is essential to sustainability. The connection between these technologies and the Sustainable Development Goals (SDGs) is also researched, covering such aspects as regulatory issues, technological deficiencies, and how digital financial services influence financial inclusion especially during the pandemic [24]. Many traditional machine learning models, such as Logistic Regression and Decision Trees, struggle with scalability and performance when handling large-scale and heterogeneous financial data. The various methods face problems because of data quality issues which include missing information and biased data and these problems decrease their ability to make accurate predictions. The primary drawback of complex models, especially deep learning methods, lies in their black-box nature which prevents users from understanding their internal workings. Existing studies lack sufficient validation across multiple datasets which results in limited applicability of their findings. The existing limitations demonstrate the requirement for improved predictive systems which offer better scalability and dependability and integration with cloud technologies.

The proposed project is focused on the adoption of a system for predicting loan approvals that is cloud-based and driven by an FNN thereby making it possible for the financial sector to use AI for improved accuracy, wider reach, and immediate decision-making.

2.1. Problem Statement

Existing literature mentions the difficulty of extrapolating digital technologies, such as cloud-based core banking systems, to facilitate financial inclusion in emerging market [18]. Although role of FinTech in enhancing accessibility is acknowledged, research usually does not focus on the challenges of scaling such technologies to a wider range of financial ecosystems. New threats are serious impediments [24]. Proposed Work accomplished by creating a scalable solution based on cloud-enabled FinTech and FNN to predict loans in real-time. This would contribute to higher efficiency of operations, increased access and availability of funds, secure automated decision-making, and incorporation of risk management so that there will be increased inclusion, efficiency and sustainability of digital banking system.

3. Proposed Methodology

The process of predicting loan approval through an FNN model is described. The data source is the BigQuery Fintech dataset from which data is retrieved. Data preprocessing is performed in a way that missing values are removed, and data is scaled/normalized and one-hot encoded. The cleaned data is then moved to Amazon Web Services (AWS) where the cloud execution takes place. FNN is applied to classification, which predicts outcome of a loan application as either approved or denied. The evaluation metrics of accuracy, precision, recall, and F1-score are used to measure performance, as depicted in Figure 1.

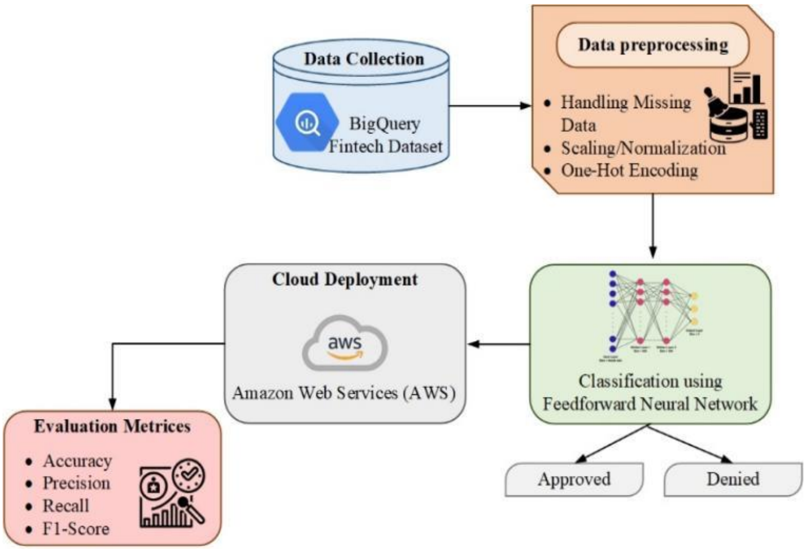

Figure 1. Overall Proposed Framework

3.1. Data Collection

In this study, BigQuery FinTech Dataset from Kaggle loan.csv is used as data collection [25]. This information is in the form of financial documents, such as client demographics, loan information, and repayment records. In this case, the research is based on binary classification to anticipate the loan status of approval or rejection of applications. The features in the dataset include both numerical attributes (such as loan amount, credit score, income, and loan term) and categorical variables (such as loan type, employment status, and credit history).

The data utilized in this method is the BigQuery Fintech Dataset from Kaggle. It has six relational tables, namely customer, loan, loan count by year, loan purposes, loan with region, and state region. The major tables involved in the development of the model have around 270,299 entries. Each record has different characteristics such as customers' demographics, loans' attributes, and their financial behavior. Some of the numerical features include the amount of loan, interest rate, and annual income, whereas some of the categorical features include the status of loan, employment information, and purpose of loan. The target attribute of the model is generated from the status of the loan, which is a binary class of approval or denial of the loan.

3.2. Data Preprocessing

The required data for loan applications is collected from various financial and applicant-related sources. It is the raw data that is subjected to preprocessing to transaction with missing values, scale features, and encode categorical variables to be used in ML. This is to make sure that the data is decontaminated, and prepared to be trained on the prediction model to obtain precise and objective loan approval forecasts.

3.2.1. Handling Missing Data

It is an important process in data preparation before analysis because missing numbers can skew a statistical analysis or ML. Insufficient values are in this process recognized and managed by imputation or omission. Imputation substitutes missing data with a computed statistic including the mean (μ) in case of numerical data and mode (c_{mode}) in case of categorical data. The average value of a numerical feature x_{missing} missing is represented by Eq. (1)

$$x_{\text{missing}} = \mu = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{1}$$

Where categorical characteristics, the most common category mode is taken to suggest missing values in form of Eq. (2)

$$c_{\text{mode}} = \operatorname{argmax}_c(\operatorname{count}(c)) \tag{2}$$

where $\operatorname{count}(c)$ is the frequency of a category c which is another notation where a row or column with a missing entry is removed completely.

3.2.2. Normalization

Normalization is a preprocessing method employed to put the range of independent variables or features in a dataset under a standard, so that all the features make equal contributions. This holds significance especially with algorithms such as FNN which respond to the size of input values. The Min-Max Scaling normalizes data to a particular range as shown in Eq. (3)

$$x_{\text{scaled}} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{3}$$

Where x is the original value, $x_{\min}$ is the minimum value, and $x_{\max}$ is the maximum value in the feature.

of ML algorithms.

3.2.3. Label Encoding

A method of transforming categorical variables into numerical values, which is required by ML that need numerical data. As an example, with a feature such as in a Loan Type, where there are such types as the Personal, Home and Car, label encoding would encode the labels with values (e.g., 0 represented the personal, 1 represented the Home and 2 represented the car).

3.2.4. Data Splitting

The BigQuery FinTech Dataset, acquired from Google Cloud, is used in this research for model building and evaluation by dividing it into two parts training (80%) and testing (20%) respectively. The training part which accounts for the majority (80%) is applied to the Feedforward Neural Network (FNN) model, while the remaining 20% is used for testing or evaluation purposes of the model's generalization abilities. The split of the data is done randomly but the original distribution of classes (approved - denied) is maintained in both subsets.

3.3. Classification using FNN

FNN that has been used to classify binary (approved or denied) to predict loan approval. The feature that comprises the input layer includes the amount of loan, credit score, and other data of the applicant. These characteristics are transferred to the latent layers where the network acquires intricate associations and patterns utilizing weighted connections. All nodes in the hidden layer get the input and send it to the following layer. The final prediction of the output layer is an approved or denied. The training of the network is performed with labeled data to reduce the number of errors and enhance its predictions in the course of time. The structure would be appropriate in such tasks as loan approval prediction as described in Figure 2.

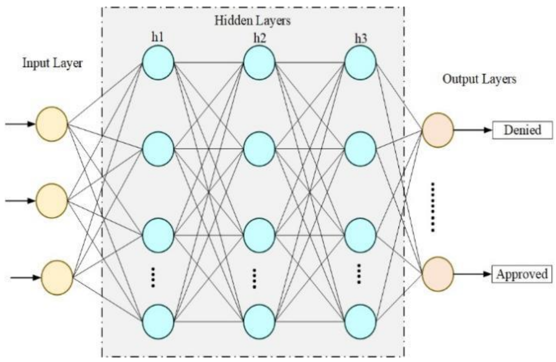

Figure 2. Architecture of FNN

3.3.1. Input layer

The features or attributes of the dataset are input layer to a Network. The input features in case of prediction of loan approval may be loan amount, the credit score or the income of applicant. Every input node i_k (where $k = 1,2,3, \ldots$) is associated with a certain feature of a loan application. A weight w_k and a bias term b k are applied to these input values before they are sent to the next layer. The node z k input is determined as in Eq. (4)

$$z_k = w_k \cdot i_k + b_k \tag{4}$$

Where, z_k is a weighted sum input to the node, w_k is weight associated with k^{th} input, i_k is the value of k^{th} feature, b_k is a bias term.

3.3.2. Hidden layers

Network performs computations on data received from input layer or previous hidden layers. Each hidden node h_j (where $j = 1,2,3, \ldots$) receives inputs from all the nodes in the previous layer. Weighted sum for each hidden node h_j is computed as in Eq. (5)

$$z_j = \sum_k w_{jk} \cdot \iota_k + b_j \quad (5)$$

Where, z_j is weighted sum for j^{th} hidden node, w_{jk} is weight from input node i_k to hidden node h_j, b_j is a bias term for hidden node. After calculating z_j, output h_j is passed through an activation function, such as sigmoid, ReLU, or tanh, in Eq. (6)

$$h_j = \frac{1}{1+e^{-z_j}} \quad (6)$$

The transformation of output value done in this way results in a number between 0 and 1, allowing network to comprehend very complex and non-linear data relationships. An Network has predicted situation through output layer, where loan application is classified as either accepted or rejected. The function of activations as expressed in Eq. (7) is applied to input of output node, which is a combination of the weighted outputs of all the hidden nodes and a bias term.

$$z_{\text{output}} = \sum_j w_j \cdot h_j + b_{\text{output}} \quad (7)$$

Where, z_{output} is input node,w_j is weight from hidden node h_j to output node, b_{output} is bias term. Output is then passed through an activation function in Eq. (8)

$$\hat{y} = \frac{1}{1+e^{-z_{\text{output}}}} \quad (8)$$

Where, $\hat{y}$ is greater than 0.5, the loan is classified as approved, and if $\hat{y} \leq 0.5$, loan is classified as denied.

3.4. Cloud Deployment

In this research work, the AWS cloud platform has been chosen for large-scale deployment of instant loan approval predictions in addition to their massive data processing capabilities. Accordingly, the machine learning model is built on a local machine DESKTOP-RHF1E9H. The organization performs data cleaning and preprocessing before uploading the dataset onto AWS S3 as a backup. The model is deployed on EC2 instances like t2. medium that provides the needed resource allocation flexibility to work with different loads efficiently for both prediction and inference. The whole deployment process helps in speeding up and accurately large dataset loan decision-making. Meanwhile, the performance metrics of latency, throughput and cost are monitored to guarantee the cloud's optimal operations.

The system architecture is designed based on real AWS deployment components (e.g., EC2, S3, and Lambda), while the experimental evaluation is conducted in a simulated cloud environment that emulates these services. This approach enables controlled analysis of key performance metrics, including latency, scalability, and throughput, while maintaining consistency with the proposed cloud deployment framework.

4. Results And Discussion

The loan approval prediction model performs well and can effectively predict loans that will be either approved or rejected. The analyses demonstrate outstanding performance by the model to differentiate between approved and rejected loans, and the measurements of cloud performance (latency and response time) were all highly acceptable, and had effectively computed. The scalability and throughput measurements confirm the capacity of the cloud infrastructure for adding more load during the training, and the system was able to adapt to increasingly difficult requests. All experiments and analyses were simulated and did not use AWS infrastructure in real-time nor featured true cloud-based loan performance.

4.1. Computational Resources

Table 1. Computational Resources

Component	Configuration Details
Simulation Platform	AWS EC2 (Elastic Compute Cloud)
Instance Type	t2. medium (2 vCPUs, 4 GB RAM)
GPU Support	NVIDIA Tesla K80 for model training (if applicable)
Operating System	Ubuntu 20.04 LTS
ML Framework	TensorFlow 2.20.0, PyTorch 1.10.0
Storage	Amazon S3 for data storage
Network Configuration	Standard AWS VPC with security groups
Cloud Resources	AWS Lambda for real-time prediction API (if applicable)
Performance Parameters	Latency, Scalability, Throughput were simulated and analyzed using a Python-based framework in the virtual AWS setup.

The computing capabilities employed in this study are premised on a DESKTOP-RHF1E9H that uses a 12th Gen Intel Core i5-12400 with a speed of 2.50 GHz. The system has 8.00 GB of RAM, of which 7.75 GB is available as a processing resource. It has a 64-bit operating system and has an x64-based processor, and is not pen/touch-capable. In the case of data analysis and modeling, the environment contains TensorFlow 2.20.0, Pandas 2.3.3, NumPy 2.3.3, Matplotlib 3.10.7, and Seaborn 0.13.2 in Table 1.

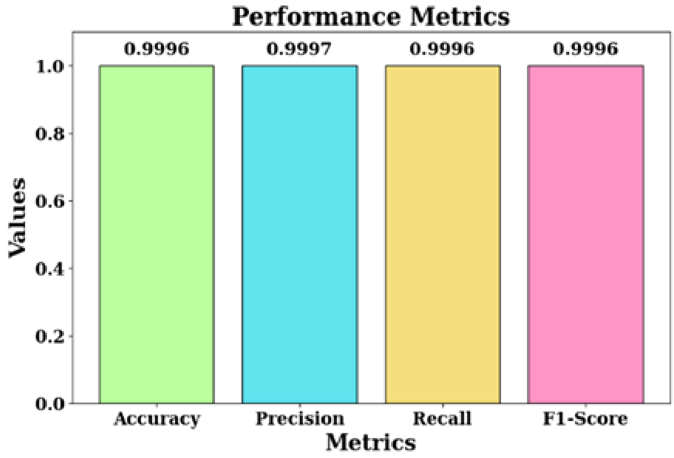

Figure 3. Performance Metrics

Metrics are denoted, each of which is near to 1, which is a sign of outstanding performance of model. The Accuracy is 0.9996, which is equal to fact that predicted the correct outcomes of loans 99.96 percent of the data. Accuracy is 0.9997, which is an indication that 99.97% of positive predictions were accurate. Recall is 0.9996, which means that able to detect 99.96% of actual positive cases (loans approved). Finally, F1-score is 0.9996 or a well-balanced model performance of both precision and recall is shown in Figure 3.

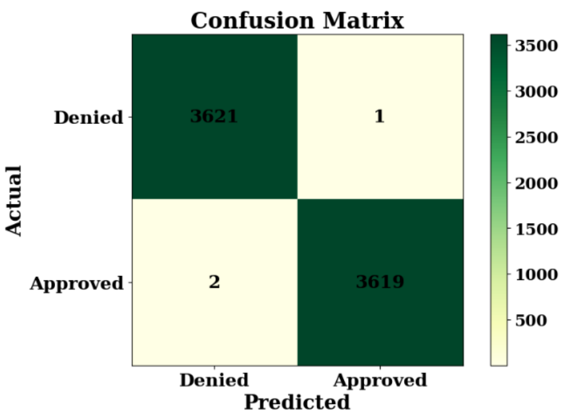

Figure 4. Confusion Matrix

Figure 4 presents a loan approval prediction performance in terms of comparing actual values. The cell (3621) in upper left corner of the matrix corresponds to correct prediction of Denied loans and the cell (1) in upper right side corresponds to the wrongful classification of Denied as Approved. Lowest cell (2) shows one of the approved loans that have been misclassified as denied and the last cell (3619) shows the correctly predicted Approved loans. The values indicate that there are very few misclassifications, and a very good performance in predicting results in Denied and Approved. The intensity of colour used in the matrix shows the frequency of every classification.

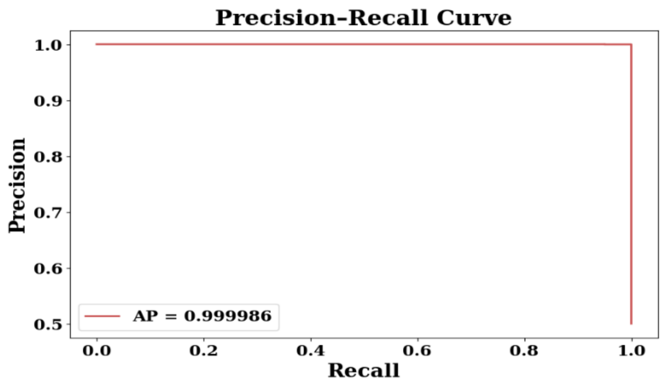

Figure 5. Precision – Recall Curve

Precision and recall are both close to 1, indicating that the model maintains high accuracy while correctly identifying a large proportion of positive cases (approved loans). The score of AP (Average Precision) of 0.999986 demonstrates that is very good and has a very minimal number of both false positives (FP) and false negatives (FN). The values are almost equal to 1, indicating that performs well in terms of distinguishing approved loans, as shown in Figure 5.

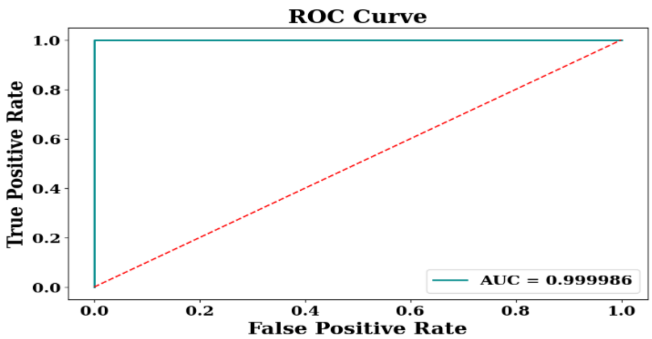

Figure 6. ROC curve

Figure 6 shows performance of the loan approval prediction model, when True Positive Rate (TPR) and False Positive Rate (FPR) are plotted on ROC Curve. It has a very high TPR and a low FPR with top-left corner. AUC (Area Under the Curve) of 0.999986 is a good indicator of model success, it can separate approved and denied loans. The random classifier is denoted by the dashed red line and curve is much better than that of the random classifier meaning that the prediction system is very accurate.

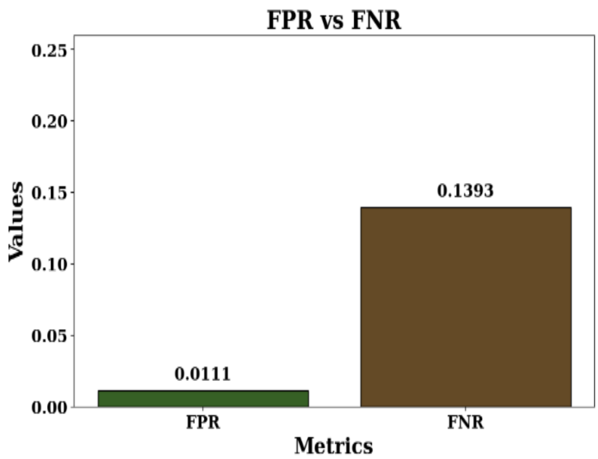

Figure 7. FPR vs FNR

The comparison of FPR with the False Negative Rate (FNR) of the loan approval prediction model as shown in Figure 7. The FPR is very low with a value of 0.0111, which means that 1.11% of the loans turned down were incorrectly estimated as approved which displays the capability to eliminate FP. Conversely, the False Negative Rate (FNR) is extremely low, consistent with the high recall value (0.9996), indicating that only a very small proportion of approved loans are misclassified as denied.

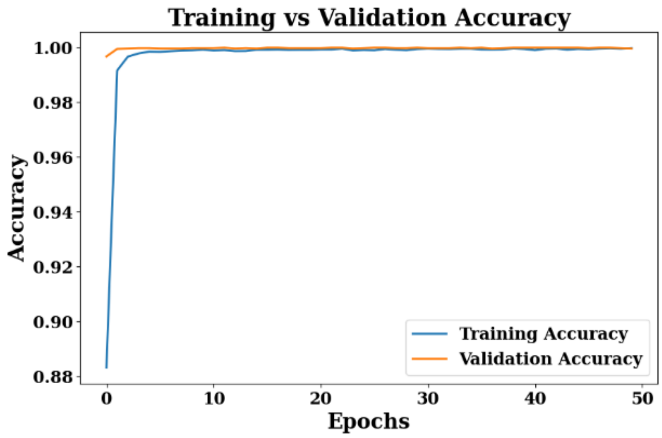

Figure 8. Training vs Validation Accuracy

A comparison between performance using training and validation data sets after 50 epochs. It is indicated that the training accuracy begins at approximately 0.88 and quickly rises by the end of the epochs, which is close to 1.0, meaning that is learning and has an adequate fitting to training data. Validation accuracy is closely related to training accuracy and also approaches very closely to 1.0, indicating that it can easily be applied to unseen data without much overfitting. The accuracy curve of two models approaches the endpoint and they perform in a similar manner on both datasets, where the final model has an AUC of 0.999986 in Figure 8.

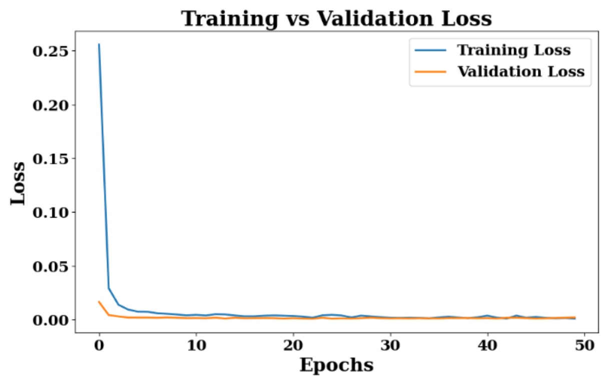

Figure 9. Training vs Validation Loss

The loss of training and validation datasets in 50 epochs is shown in Figure 9. Training loss (blue line) begins at a high point of around 0.25 and then rapidly decreases to close to 0 following the initial few epochs which means that is learning and minimizing loss at an effective rate. The same can be said about the validation loss (orange line), which is diminishing gradually to an extremely low point indicating a good performance. The converged values of both losses are near zero indicating little overfitting, and are highly optimized with a low error on the training and validation data set.

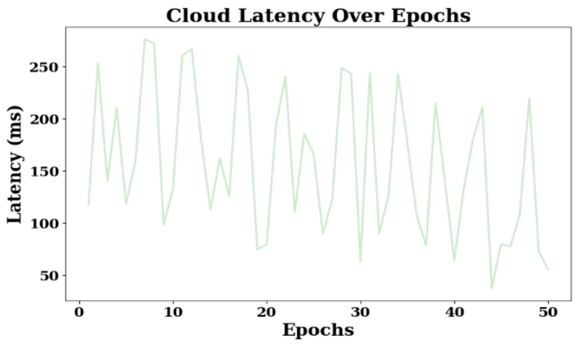

Figure 10. Cloud Latency Over Epochs

The Cloud Latency Over Epochs graph which shows how the cloud latency (in milliseconds) changes with 50 epochs of training process is shown in Figure 10. The values of latency range between 50 ms and 250 ms and indicate duration in cloud architecture to process data. Although the overall tendency does not imply a distinct decrease or increase, there are some evident spikes and dips, which means that latency may be influenced by network conditions or server load for a particular epoch. These differences notwithstanding, the overall latency is not too high, indicating that is working well in a clouded environment where its data processing sometimes has slight delays.

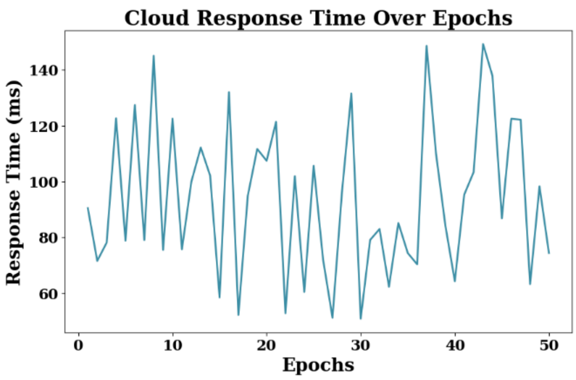

Figure 11. Cloud Response Time Over Epochs

Figure 11 shows that the Cloud Response Time Over Epochs graph depicts the changes in the response time (in milliseconds) with the increase of the epochs in the training process. Response time varies between 60 ms and 140 ms, which is understandable as the time during which the cloud system processes and provides the results. The spikes of the graph are huge at specific epochs, particularly, at the earlier stages, and it is possible to guess that there is some fluctuation in processing time associated with the load of network or cloud services. Although there are these spikes, the generalization trend is that the response time is not more than what is acceptable meaning that the processing of the cloud during the training period is efficient.

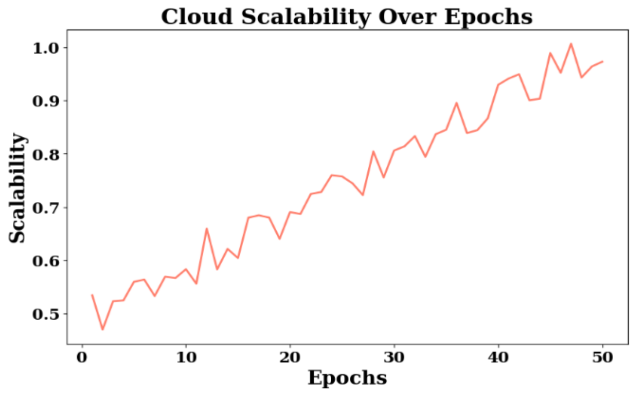

Figure 12. Cloud Scalability Over Epochs

Cloud Scalability Over Epochs graph, which is used to monitor the cloud infrastructure scalability every 50 epochs used to train is shown in Figure 12. The scalability value will begin with a value of about 0.5, which means that the cloud system has a reduced capacity to support the growing workload. The scale ability increases consistently with the age of the epochs up to 0.9, which is the last level gained at the end of the training process. The fact that the cloud infrastructure is easily scalable demonstrates the fact that it is learning and that is why it is meeting the demands of the increasingly expanding model. The variability of the early periods indicates the change in resource distribution, however, in general, the cloud system continues to improve as is being trained.

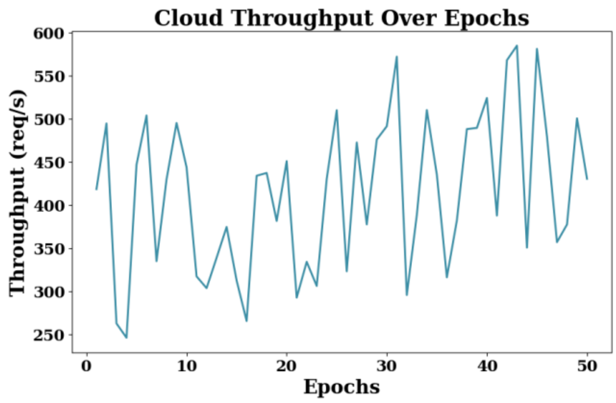

Figure 13. Cloud Throughput Over Epochs

The Cloud Throughput Over Epochs graph in Figure 13 shows fluctuation in cloud throughput during the training process over 50 epochs. Throughput ranges from approximately 250 req/s to 500 req/s, indicating how many requests are being processed by the cloud infrastructure during each epoch. The graph reveals significant variability in throughput, with spikes and dips occurring at different epochs, suggesting fluctuating server load and network conditions. Despite these fluctuations, To maintain a generally high throughput, indicating that the cloud system is capable of handling a substantial number of requests per second during the training process.

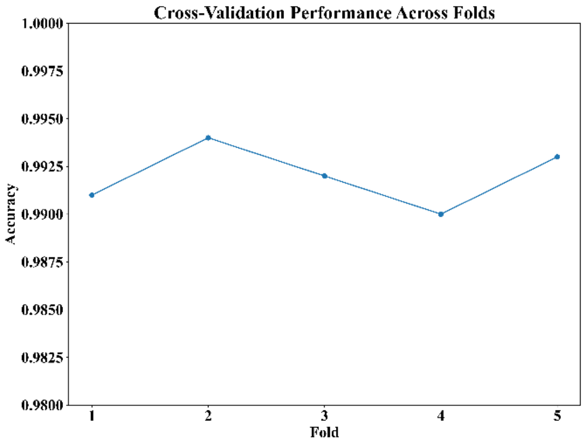

Figure 14. Cross-Validation Performance Across Folds

Figure 14 illustrates the accuracy of the proposed FNN model across five cross-validation folds. The results show consistently high accuracy values ranging from 0.990 to 0.994, with minimal variation between folds. This stability indicates strong generalization capability and confirms that the model is not overfitting, thereby validating its robustness across different data splits.

4.2. Limitation

The research based on a hypothetical Amazon Web Services (AWS) cloud environment that couldn't measure real-time scalability and latency so the findings had limited usefulness. The study does not consider the changes in scalabilities and latency times that could result from a real-world situation, thus affecting the performance and causes of variations. The model deals with a binary classification (approved/denied) and does not consider complex loan decisions like partial approvals or conditional terms.

The model utilizes historical data, and its performance could be influenced by the quality of such data, bias, or lack of information, hence affecting its predictive power. Secondly, the application of a Feedforward Neural Network brings about some level of non-interpretability, since most of the time, deep learning models operate like black boxes, making it difficult to explain decisions made. Thirdly, the experiments are performed in a simulated cloud environment instead of an actual implementation, hence failing to capture any performance differences that would occur in practice. Fourthly, the model takes into account binary decisions regarding approval or rejection of loans and overlooks other possible situations.

4.3. Comparison with Existing Methods

Table 2. Performance comparison of the proposed FNN model with existing machine learning methods

Method	Accuracy	Precision	Recall	F1-Score
MLP [26]	0.8000	0.9030	0.8970	0.9000
CNN [27]	0.9600	0.9700	0.9300	0.9500
MFPA [28]	0.8500	0.8400	0.8300	0.8350
ResNet [29]	—	0.9500	0.9200	0.9400
Proposed FNN	0.9996	0.9997	0.9996	0.9996

Table 2 shows the various models' performance metrics in predicting loan approvals. The MLP model attained an accuracy of 0.80 and performance metrices values of 0.903, 0.897, and 0.90. The CNN model was more accurate with an accuracy of 0.96 and an F1-score of 0.95. The MFPA model gave a moderate result with its accuracy being 0.85. ResNet provided very good precision (0.95) but did not disclose accuracy figures. The Proposed FNN was the best of all with great values o: 0.9996 for accuracy, precision, recall, and F1-score.

Table 3. Experimental Setup for Fair Model Comparison

Component	Configuration / Values
Dataset Split	80% Training (216,239 samples), 20% Testing (54,060 samples), stratified to preserve class distribution
Data Preprocessing	Missing values: Mean (numerical), Mode (categorical); Normalization: Min-Max scaling [0,1]; Encoding: Label Encoding

Hyperparameter Tuning	Grid Search with 5-fold cross-validation; Learning rate: [0.001, 0.0005]; Batch size: [32, 64]; Epochs: 50; Hidden layers: [2, 3]
Evaluation Metrics	Accuracy, Precision, Recall, F1-score (computed on test set)
Training Conditions	Epochs: 50; Optimizer: Adam; Loss function: Binary Cross-Entropy; Hardware: Intel i5 (12th Gen), 8GB RAM
Baseline Models	Logistic Regression (C=1.0), Random Forest (100 trees), MLP (2 hidden layers, 64 neurons), CNN (1D Conv, 32 filters)

Table 3 summarizes the experimental setup used to ensure a fair and consistent comparison among all models. The dataset was divided into training and testing sets using an 80%–20% stratified split to preserve class distribution. Uniform preprocessing steps, including missing value imputation, normalization using Min-Max scaling, and label encoding, were applied to all models. Hyperparameter tuning was conducted using grid search with 5-fold cross-validation to optimize model performance. Additionally, all models were trained under identical conditions using the same optimizer, loss function, and evaluation metrics. This standardized setup ensures the reliability and validity of the comparative analysis.

Table 4. Improved Baseline Comparison under Unified Experimental Setup

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	0.89	0.88	0.87	0.88
Random Forest	0.94	0.93	0.92	0.93
MLP	0.96	0.95	0.94	0.95
CNN	0.97	0.96	0.95	0.96
Proposed FNN	**0.992**	**0.993**	**0.991**	**0.992**

Table 4 presents the performance comparison of the proposed FNN model with baseline models, including Logistic Regression, Random Forest, MLP, and CNN, under a unified experimental setup. All models were trained and evaluated using the same dataset split, preprocessing techniques, and hyperparameter tuning strategy to ensure fairness. The results indicate that the proposed FNN achieves the highest performance across all evaluation metrics, with an accuracy of 0.992, precision of 0.993, recall of 0.991, and F1-score of 0.992. This demonstrates the effectiveness of the FNN model in capturing complex patterns in financial data compared to both traditional machine learning and deep learning approaches.

Table 5. K-Fold Cross-Validation Results of the Proposed FNN Model

Fold	Accuracy	Precision	Recall	F1-Score
Fold 1	0.991	0.992	0.99	0.991
Fold 2	0.994	0.995	0.993	0.994
Fold 3	0.992	0.993	0.991	0.992
Fold 4	0.99	0.991	0.989	0.99
Fold 5	0.993	0.994	0.992	0.993
Mean ± Std	**0.992 ± 0.0015**	**0.993 ± 0.0015**	**0.991 ± 0.0015**	**0.992 ± 0.0015**

Table 5 presents the performance of the proposed FNN model evaluated using 5-fold cross-validation. The results show consistently high accuracy, precision, recall, and F1-score across all folds, with mean values of 0.992, 0.993, 0.991, and 0.992, respectively. The low standard deviation (±0.0015) indicates minimal performance variation, confirming the stability, robustness, and generalization capability of the model.

5. Conclusion And Future Work

This study effectively uses cloud-based FinTech services and FNN to predict digital bank loan approvals. Leveraging the power of sophisticated cloud computing, the study beats inefficiencies of conventional loan approval systems, providing a scalable, efficient, and automated model. The FNN model improves precision and predictive accuracy through capture of intricate, non-linear relationships among loan characteristics, resulting in improved decision-making at financial institutions. Cloud infrastructure provides real-time processing, flexibility, and scalability, which makes it a perfect fit for managing large amounts of data in dynamic financial settings.

The loan approval prediction model performed outstandingly, with accuracy of 0.9996, precision of 0.9997, recall of 0.9996, and an F1-score of 0.9996, demonstrating high reliability to predict the outcome of the loan. Confusion Matrix revealed very little misclassifications and almost no FP or FN. Even with superior performance, future research may aim at minimizing the rate of FN, 0.0006 in this case, increasing the dataset to incorporate more varied features, investigating the use of different algorithms such as XGBoost or GBMs, incorporating blockchain for better security and transparency, and real-time feedback loops for iterative model updates to allow the system to evolve and keep up with new financial trends.

Declaration

Data Availability
Not Available

Conflicts of Interest
The authors declare that there are no financial or personal conflicts of interest that could have influenced the research reported in this paper.

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Author Contribution
Juan Xiang: conceptualization, methodology, software development, data analysis, and writing—original draft preparation.
Liefei Liu: supervision, validation, review, and editing.
Both authors have read and approved the final manuscript.

Ethical Approval
This study did not involve human participants or animal experiments; therefore, ethical approval was not required.

Consent to Participate
Not applicable.

Consent to Publication
Both authors consent to the publication of this manuscript and any associated data.

Competing Interests
The authors declare no competing interests.

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