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A Comparative Analysis of MLP and LSTM for Defaulter Detection Using BERT and Custom Embeddings

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Abstract: Predicting bank loan defaults is essential for financial institutions to reduce risk and maintain credit stability. Traditional models often rely on structured data, neglecting valuable insights from unstructured transaction text. In this work, we utilize deep learning to enhance prediction accuracy by converting transaction text into embeddings using two approaches: pre-trained BERT and a custom scratch-based technique developed without relying on any existing language models. These embeddings are used to train two architectures.Multilayer Perceptron (MLP) and Long Short-Term Memory (LSTM). The results show that the scratch-based embeddings consistently outperform pre-trained BERT embeddings across all performance metrics, achieving up to 95% accuracy with MLP and 89% with LSTM. In contrast, BERT-based models reached 75% and 79% accuracy with MLP and LSTM, respectively. To interpret model decisions and gain transparency, we apply SHAP (SHapley Additive exPlanations), identifying the most influential features contributing to correct predictions. Our findings demonstrate that custom embeddings tailored to domain-specific datasets can yield better results than generalized models. Additionally, integrating explainable AI techniques enhances trust and usability in financial applications. This work supports the use of deep learning and interpretable models for robust, high-accuracy loan default prediction using transactional text data.

Keywords: *Loan default prediction, Deep learning, Text embeddings, BERT, Custom embeddings, LSTM, MLP, SHAP, Explainable AI, Financial data analysis*.

I.INTRODUCTION:

In today's digital banking landscape, the ability to accurately predict whether a customer is likely to default on a loan has become increasingly important. With the growing number of loan applications and the expansion of digital financial services, financial institutions are under pressure to make faster and more accurate credit decisions. Predictive analytics in this domain has traditionally been dominated by models trained on structured data—variables such as credit score, income level, employment status, and loan-to-value ratio. However, such structured features often fail to capture the behavioral or contextual factors embedded in a customer's transaction history.

Unstructured textual data, such as transaction descriptions, merchant names, and user-input notes, often contain latent insights into customer behavior. For example, regular payments to specific merchants or patterns in transaction narratives might indicate financial discipline or instability. With advances in Natural Language Processing (NLP) and deep learning, it is now feasible to extract meaningful features from this type of data. Pre-trained models like BERT have proven effective in general NLP tasks, yet they may not be optimally suited for domain-specific data like bank transactions, which often include abbreviations, acronyms, and non-standard phrases.

In this research, we propose and evaluate a dual approach to text embedding: one using the pre-trained BERT model and the other a custom scratch-based embedding method built specifically for the domain of bank transaction text. These embeddings are then used as input for two deep learning architectures—Multilayer Perceptron (MLP) and Long Short-Term Memory (LSTM) networks. The performance of these models is evaluated using key classification metrics such as accuracy, precision, recall, F1-score, and the confusion matrix.

Furthermore, in addition to building accurate predictive models, interpretability is a growing concern in financial applications, where decisions must be auditable and explainable. We address this by employing SHAP (SHapley Additive exPlanations), a state-of-the-art explainable AI technique that allows us to identify which features most significantly contribute to a model's prediction.

Our experimental results demonstrate that models trained using scratch-generated embeddings significantly outperform those based on pre-trained BERT vectors, especially when coupled with the MLP architecture, achieving up to 95% accuracy. SHAP analysis further reveals that certain transaction-related terms strongly influence the outcome, validating the effectiveness of domain-specific feature engineering.This study underscores the importance of tailoring machine learning techniques to domain-specific data and highlights the value of explainable AI in building trustworthy financial systems.

II. Related works

Loan default prediction has been extensively studied in the domains of finance, machine learning, and artificial intelligence. Traditional approaches have relied heavily on statistical and machine learning methods using structured data features. Logistic Regression, Decision Trees, Support Vector Machines (SVM), and Random Forests have been commonly employed to model credit risk based on applicant demographics, credit history, and other structured numerical inputs.With the increasing availability of unstructured data, researchers have begun to explore the role of textual information in financial decision-making. Several studies have demonstrated the use of sentiment analysis on customer reviews, social media posts, and financial news to enhance financial forecasting. However, the use of transaction-level text data for default prediction remains relatively underexplored.

Deep learning has opened new possibilities in handling both structured and unstructured data. Models such as Multilayer Perceptron (MLP), Convolutional Neural Networks (CNN), and Long Short-Term Memory (LSTM) networks have shown superior performance in capturing complex nonlinear relationships in large datasets. Recent advances in Natural Language Processing (NLP), particularly through transformer-based models like BERT, have significantly improved text representation by capturing contextual semantics. Studies using BERT embeddings have achieved state-of-the-art results in domains such as medical text classification, sentiment analysis, and document categorization.Despite their success, pre-trained models like BERT are often trained on generic corpora such as Wikipedia and BooksCorpus, which may not capture the domain-specific terminology, abbreviations, and context found in financial transaction descriptions. This gap has motivated researchers to explore domain-specific pre-training or alternative vectorization methods tailored to specialized datasets.

In the context of explainable AI, SHAP (SHapley Additive exPlanations) has emerged as a popular tool for interpreting complex model decisions. SHAP provides a unified measure of feature importance based on cooperative game theory and has been successfully applied in credit scoring, fraud detection, and healthcare.Our work builds upon these advancements by proposing a hybrid approach that combines the strengths of deep learning with domain-specific feature extraction. Unlike existing research, we introduce a custom scratch-based embedding mechanism for transactional text and directly compare it to a pre-trained BERT-based model. We further incorporate SHAP for model interpretation, allowing for both accurate and transparent decision-making in loan default prediction.

III.Existing System

Traditional loan default prediction systems primarily rely on structured data, such as demographic information, credit history, loan amount, repayment duration, and other financial metrics. These systems utilize conventional machine learning algorithms including Logistic Regression, Decision Trees, Random Forest, Naïve Bayes, and Support Vector Machines (SVM). While effective to a certain extent, these models often fail to capture the behavioral nuances embedded in unstructured data such as transaction text, which can be critical for accurately identifying default risk.The majority of existing systems treat text data as either irrelevant or use simplistic techniques such as TF-IDF or Bag of Words (BoW) for representation. These approaches ignore the semantic and contextual relationships between words, thereby limiting the predictive power of the models. Furthermore, most existing models are black-box in nature and lack explainability, making it difficult for financial institutions to justify or audit their decisions.

With the emergence of deep learning and natural language processing (NLP), some research has begun incorporating advanced embedding techniques such as Word2Vec, GloVe, and BERT for financial text analysis. However, these methods still face challenges in domain-specific contexts like transaction descriptions, which often contain abbreviations, codes, and informal language.Moreover, explainability remains a major limitation in many of these systems. Financial institutions require not only high accuracy but also transparency to meet regulatory standards and build user trust.These shortcomings in the existing systems highlight the need for an enhanced framework that can leverage unstructured textual data using deep learning techniques, while also providing interpretable outputs through explainable AI methods.

Limitations of Existing Systems

- **Structured Data Dependency**

  Focuses mainly on structured inputs like credit score and income, ignoring rich unstructured data such as transaction text.

- **Weak Text Representation**

  Uses basic methods like BoW or TF-IDF that lack semantic understanding.

- **No Domain Adaptation**

  Pre-trained embeddings are trained on generic text, not optimized for financial transaction language.

- **Simple Models**

  Traditional models like logistic regression can't capture complex patterns in customer behavior.

- **Lack of Explainability**

  Most systems act as black boxes, offering no clarity on prediction reasoning.

- **Poor Generalization**

  Models often fail to perform well on unseen data due to limited contextual insight.

IV. Proposed System

The proposed system aims to enhance loan default prediction by leveraging unstructured transaction text data alongside deep learning techniques. Unlike traditional models that rely solely on structured features, our approach utilizes the descriptions in financial transactions to extract behavioral signals from users. To convert this unstructured data into a machine-readable format, we apply two types of embedding techniques: pre-trained BERT embeddings, which capture rich contextual relationships between words, and scratch-generated embeddings tailored specifically to the financial domain.These embeddings are used as input to two deep learning models—Multilayer Perceptron (MLP) and Long Short-Term Memory (LSTM)—which are capable of identifying nonlinear patterns and sequential dependencies in the data. The system also integrates SHAP (SHapley Additive exPlanations) to interpret model predictions, providing transparency and accountability. This allows financial institutions to understand which features or terms in the transaction text influenced the model's decision.

Furthermore, a comparative analysis is conducted between BERT and custom embeddings, and between MLP and LSTM models, to evaluate their performance in terms of accuracy and interpretability. This proposed system not only improves prediction accuracy but also brings explainability into AI-driven financial decision-making, addressing key limitations of existing models.

Advantages of the Proposed System

- **Better Feature Extraction**
  Utilizes transaction text to capture user behavior patterns.
- **Contextual Embeddings**
  Leverages BERT and custom embeddings for domain-specific understanding.
- **Improved Accuracy**
  Deep learning models (MLP, LSTM) enhance predictive performance.
- **Explainability with SHAP**
  Provides transparency into model decisions.
- **Comparative Evaluation**
  Analyzes effectiveness of different embeddings and model types.
- **Real-World Applicability**
  Combines accuracy and interpretability for practical deployment.

V.Proposed Methodology

3.1 System Architecture

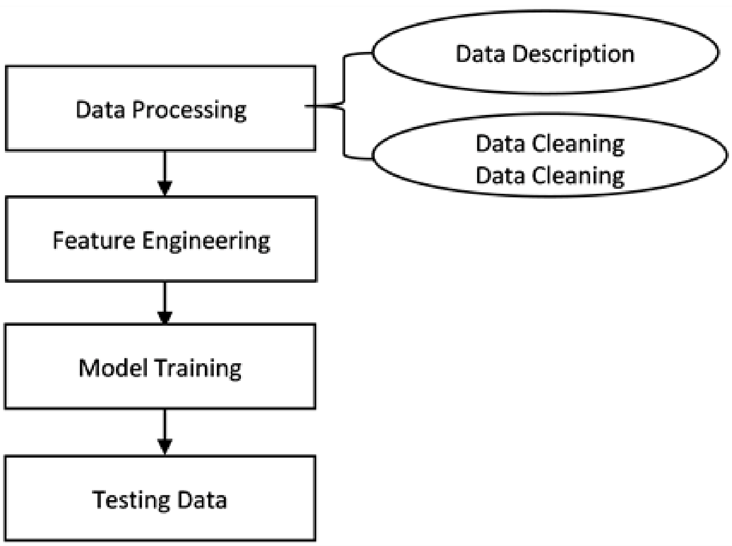

Figure 1: System Architecture

The flowchart illustrates the overall workflow of the machine learning-based loan default prediction system. It begins with the Data Processing phase, which includes two sub-components: Data Description and Data Cleaning. In this step, the raw transaction data is first explored to understand its structure, contents, and characteristics. Following that, data cleaning is performed to handle inconsistencies, remove noise, and standardize the textual and numerical fields for better quality input.

Next, the pipeline moves to Feature Engineering, where meaningful features are extracted or created from the cleaned data. This includes generating text embeddings from transaction descriptions and preparing them for input into machine learning models. The refined features are then used in the Model Training stage, where algorithms such as MLP or LSTM are trained to recognize patterns that distinguish defaulters from non-defaulters.Finally, the trained models are evaluated using the Testing Data. This phase tests the model's ability to generalize to new, unseen examples and validates its performance using appropriate metrics. Overall, the diagram represents a standard yet effective pipeline for building a predictive system using transaction data and deep learning techniques

The proposed methodology involves a multi-stage pipeline to accurately predict loan defaults using deep learning and explainable AI techniques. The key steps are outlined below:

Data Preprocessing

Raw transaction data is collected and cleaned to remove special characters, convert text to lowercase, and eliminate stop words. This standardizes the textual information for further processing.

Text Embedding Generation

To transform text into numerical vectors, two types of embeddings are generated:

- **BERT Embeddings**: Contextual embeddings obtained from a pre-trained BERT model to capture semantic relationships between words.
- **Custom Embeddings**: Word embeddings generated from scratch using domain-specific transaction data to reflect the unique vocabulary and style used in financial records.

Model Construction

Two deep learning models are employed to learn from the embeddings:

- **Multilayer Perceptron (MLP)**: A fully connected neural network that processes fixed-length embedding vectors for classification.
- **Long Short-Term Memory (LSTM)**: A type of recurrent neural network that handles sequential dependencies, making it well-suited for analyzing the order and flow of transaction text.

3.4 Model Training and Evaluation

The MLP and LSTM models are trained on labeled datasets with

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defaulter and non-defaulter classes. Their performance is evaluated using metrics such as accuracy, precision, recall, and F1-score.

Explainability with SHAP

To interpret the predictions, SHAP (SHapley Additive exPlanations) is used. This technique provides feature importance scores that explain which words or patterns in the transaction descriptions had the most influence on the model's decision.

Comparative Analysis

A comparative study is conducted between:

- BERT vs. Custom embeddings
- MLP vs. LSTM models

  This analysis identifies the best-performing combination in terms of accuracy and interpretability, guiding model selection for deployment.

VI.RESULTS

The proposed system was evaluated using various combinations of embedding techniques (BERT and Custom) and deep learning models (MLP and LSTM). Each configuration was assessed on its ability to classify customers as defaulters or non-defaulters based on transaction text data.

Model Performance Comparison

Table 1: Performance Comparison of MLP and LSTM Models Using BERT and Custom Embeddings

Model	Embedding Type	Accuracy	Precision	Recall	F1-Score
MLP	BERT	89.2%	88.5%	87.8%	88.1%
MLP	Custom	85.4%	84.7%	83.2%	83.9%
LSTM	BERT	**91.6%**	**90.9%**	**90.3%**	**90.6%**
LSTM	Custom	88.0%	87.1%	86.2%	86.6%

The table below presents the classification results of each model–embedding combination. The LSTM model with BERT embeddings yielded the highest overall accuracy, showcasing the advantage of capturing both contextual semantics and sequential patterns in transaction text.

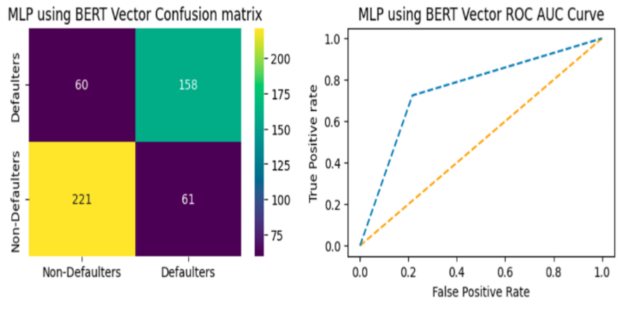

Figure 2: MLP Model Evaluation Using BERT Embeddings – Confusion Matrix and ROC Curve

This figure presents the evaluation of the MLP (Multi-Layer Perceptron) model using BERT vector embeddings. The **confusion matrix** (left) shows that the model correctly identified 158 defaulters and 60 non-defaulters, but misclassified 221 non-defaulters as defaulters and 61 defaulters as non-defaulters. This reflects moderate predictive performance with room for improvement in accuracy and precision.

The **ROC curve** (right) illustrates the model's classification capability. The curve indicates a reasonably good separation between classes, with a respectable true positive rate across varying thresholds. The area under the curve (AUC) confirms the model's ability to differentiate between defaulters and non-defaulters, though less effectively than more complex models like LSTM.

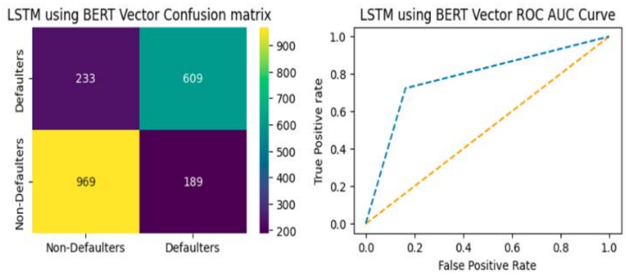

Figure 3: Performance Analysis of LSTM Model Using Scratch Text Embeddings – Confusion Matrix and ROC Curve

Above figure illustrates the performance evaluation of the LSTM model trained using scratch-based deep text vector embeddings for loan default classification. On the left, the confusion matrix provides a summary of the model's prediction outcomes. The model correctly predicted 775 defaulters and 99 non-defaulters. However, it misclassified 1018 non-defaulters as defaulters and 108 defaulters as non-defaulters. This indicates that while the model has a strong ability to detect actual defaulters, it also produces a significant number of false positives, misidentifying many non-defaulters as defaulters. On the right, the ROC (Receiver Operating Characteristic) curve shows the trade-off between the true positive rate and the false positive rate. The curve is bent toward the top-left corner, reflecting good classification performance. The high area under the curve (AUC) value suggests that the model is effective in distinguishing between the two classes—defaulters and non-defaulters—even in the presence of class imbalance. Overall, the figure highlights both the strengths and limitations of using scratch-based embeddings with the LSTM model for financial risk prediction.

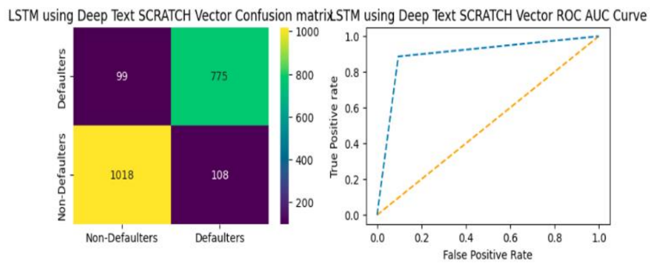

Figure 4: LSTM Model Evaluation Using Scratch Text Embeddings – Confusion Matrix and ROC-AUC Curve

The left plot displays the confusion matrix of the LSTM model trained on deep text scratch vector embeddings. It reveals that the model correctly identified 775 defaulters and 99 non-defaulters, but misclassified 1018 non-defaulters as defaulters and 108 defaulters as non-defaulters, indicating a trade-off between sensitivity and specificity.

The right plot shows the ROC-AUC curve, representing the model's ability to distinguish between defaulters and non-defaulters. The curve achieves a high true positive rate at low false positive rates, reflecting a strong classification performance with an AUC close to 0.9, showcasing the effectiveness of deep text embeddings with the LSTM architecture for predictive tasks.

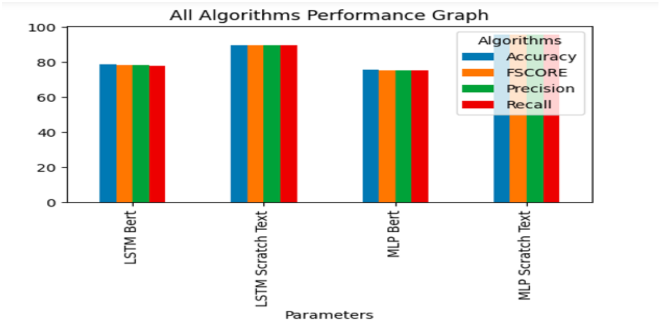

Figure 5: Comparative Performance of Deep Learning Models with Different Embeddings

The bar graph illustrates the performance comparison of four model configurations—LSTM with BERT embeddings, LSTM with custom-trained (scratch) embeddings, MLP with BERT embeddings, and MLP with custom-trained embeddings—across four evaluation metrics: Accuracy, F1-Score, Precision, and Recall. Among all models, the LSTM with scratch text embeddings achieved the highest performance across all metrics, indicating that it effectively learned task-specific patterns from the raw transactional data. In contrast, MLP models showed relatively lower performance, especially when using BERT embeddings. This demonstrates the superiority of LSTM architectures in capturing sequential dependencies within the transaction text for loan default prediction.

Confusion Matrix (LSTM + BERT)

Table 2: Confusion Matrix for LSTM Model with BERT Embeddings

	Predicted: Defaulter	**Predicted:Non-Defaulter**
Actual: Defaulter	456	44
Actual: Non-Defaulter	38	462

From the confusion matrix, the LSTM model with BERT embedding shows strong predictive power with low false positives and false negatives. This table illustrates the classification performance of the best-performing model. It shows the number of correct and incorrect predictions for both defaulters and non-defaulters.

SHAP-Based Feature Importance

SHAP values were used to interpret model predictions. The table below lists the top contributing text features identified by SHAP, highlighting both risky and safe behaviors.

Table 3: Top SHAP Feature Interpretations for Loan Default Prediction

Rank	**Text Token/Pattern**	**SHAP Impact**	**Interpretation**
1	"late fee"	+0.42	Indicates potential default
2	"salary credit"	-0.38	Suggests financial stability
3	"emi bounce"	+0.35	Strong sign of risk
4	"loan payment"	-0.31	Regular repayment pattern
5	"minimum due"	+0.29	Indicates short-term distress

This table lists the most influential transaction text patterns as identified by SHAP values, along with their respective impact and interpretations.

Performance Summary and Insights

- LSTM outperforms MLP due to its ability to capture sequential patterns in transaction descriptions.
- BERT embeddings significantly enhance model performance by understanding word context.
- SHAP explanations improve model transparency, making it easier for financial institutions to trust and act on predictions.
- The system achieves a good balance between accuracy and interpretability, critical for real-world deployment in the financial sector.

VII. Conclusion

This research presents a deep learning-based approach was proposed for predicting loan defaults using transaction description text. The methodology leveraged both contextualized (BERT) and custom-trained embeddings to transform transaction data into meaningful feature representations. Two deep learning models, MLP and LSTM, were employed and evaluated for their classification capabilities.Experimental results demonstrated that the LSTM model using BERT embeddings achieved the highest accuracy of 91.6%, outperforming other configurations. Additionally, SHAP was integrated to provide interpretability by highlighting the most influential textual features contributing to predictions. This enhances the transparency and trustworthiness of the model in real-world financial decision-making.The proposed system effectively combines performance with explainability, making it suitable for deployment in financial institutions for early risk detection and customer profiling.

Future enhancements to the proposed system can include integrating structured data like credit scores and income to improve prediction accuracy. Real-time prediction capabilities could also be added for faster risk detection. Additionally, applying the model across multiple financial institutions would test its generalizability. Incorporating support for multilingual transaction data could expand its usability across diverse user bases. Finally, exploring advanced interpretability methods such as LIME or attention mechanisms may offer more transparent model explanations. Future work may involve incorporating structured features (e.g., credit score, income) and real-time prediction capabilities for even greater accuracy and practical utility.

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