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A Comparative Study of TabTransformer and Temporal Fusion Transformer for Loan Approval Prediction Using Static and Temporal Financial Features

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Abstract: In the banking and financial services industry, loan approval is an important process that helps minimize credit risk and increase lending efficiency. Traditional machine-learning models can struggle to represent complex interactions among customer financial features and changes in financial activity over time. This paper presents a comparative study of two transformer-based deep-learning models - TabTransformer and Temporal Fusion Transformer (TFT) - for intelligent loan approval prediction. TabTransformer learns meaningful representations from structured customer data, whereas TFT is trained using twelve months of sequential financial data to model long-term financial patterns. For a fair comparison, both models are trained and tested using the same enhanced loan dataset, preprocessing pipeline and experimental setting. Performance is assessed using accuracy, precision, recall, F1-score, ROC-AUC and confusion-matrix analysis. The results show that TFT achieves 94.75% accuracy compared with 93.13% for TabTransformer, indicating that temporal financial information provides additional predictive value for automated loan application decision-making.

Keywords: Loan Approval Prediction, Tab Transformer, Temporal Fusion Transformer, Deep Learning, Credit Risk Assessment, Financial Data Analytics, Transformer Networks, Sequential Learning, Artificial Intelligence.

I. INTRODUCTION

Loan approval prediction is a critical application of Artificial Intelligence (AI) in banking and financial services because lending institutions must assess repayment capacity while controlling the risk of default. Manual assessment of a large number of applications is time-consuming, can be inconsistent, and may be affected by human judgement. Intelligent decision-support systems can analyse customer financial characteristics and help improve the effectiveness, transparency and consistency of loan approval workflows **[1]**, **[2]**.

Recent developments in machine learning and deep learning have introduced transformer architectures for structured and sequential financial data. Unlike conventional models that process features independently or rely on fixed feature transformations, transformer models use attention mechanisms to learn interactions among features and long-term relationships **[3]**, **[4]**. TabTransformer is suitable for structured financial attributes such as income, employment type, education, credit score, loan amount, EMI and repayment history. Temporal Fusion Transformer is designed to model temporal information and can learn changes in customer financial behaviour across multiple time steps.

Although transformer-based methods have reported strong performance for credit-risk assessment, existing studies often compare a transformer with conventional machine-learning models or investigate only one transformer architecture **[5]-[7]**. A direct comparison of TabTransformer and TFT using the same dataset, preprocessing methods, feature engineering and evaluation metrics is comparatively limited. This paper addresses that gap by comparing both architectures using structured customer information and twelve months of sequential financial records. The models are evaluated using Accuracy, Precision, Recall, F1-Score, ROC-AUC and confusion-matrix analysis.

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II. LITERATURE REVIEW

Jha et al. **[8]** proposed a fairness-aware deep-learning framework for loan approval prediction. Their work emphasized transparency, consistency and the reduction of bias in automated credit assessment, demonstrating that predictive performance should be considered together with fairness in financial decision-making.

Hartomo et al. **[5]** introduced a weighted-loss TabTransformer integrated with Explainable Artificial Intelligence (XAI) for imbalanced credit-risk datasets. Their results showed that transformer-based architectures can capture complex relationships among structured financial variables while supporting interpretable predictions.

Li and Li **[1]** investigated financial, demographic and behavioural factors involved in loan approval decisions. Their study highlighted the importance of preprocessing and feature engineering in improving predictive accuracy and model reliability.

Ye et al. **[6]** developed credit-behaviour scorecards based on TabTransformer and model interpretability. The work demonstrated the ability of attention-based models to analyse structured financial data and learn interactions among customer attributes.

Qiu et al. **[2]** proposed a deep-learning approach for predicting loan repayment capacity using economic and behavioural information, showing that financial patterns provide useful information for credit-risk assessment. Paul et al. **[9]** studied robustness and security issues in credit scoring under adversarial settings.

Raliphada et al. **[7]** reviewed transformer-based approaches for credit-risk prediction and concluded that attention mechanisms can improve feature representation and predictive performance. These studies motivate the present comparison of TabTransformer and TFT under identical experimental conditions.

III. METHODOLOGY

The proposed study compares TabTransformer and Temporal Fusion Transformer for intelligent loan approval prediction. TabTransformer is trained on structured customer financial attributes, whereas TFT learns temporal patterns from twelve months of sequential financial records. The same preprocessing and evaluation procedures are used for both models to maintain consistency.

A. Dataset

The enhanced loan approval dataset contains structured and sequential customer financial records. Static attributes used by TabTransformer include Age, Employment Type, Education, Annual Income, Loan Amount, EMI, Credit Score, Property Area and Repayment History. The sequential representation used by TFT contains twelve months of Income, Expenses, Savings, EMI, Credit Utilization and Repayment History. These complementary views allow the experiment to compare feature relationships in static data with long-term patterns in temporal data.

B. Data Preprocessing

Both model pipelines use the same core preprocessing procedure. Missing values are handled before training, categorical attributes are label encoded, numerical attributes are normalized or scaled, and the data are divided into training and testing sets. Applying a common preprocessing pipeline reduces differences caused by data preparation and makes the model comparison more consistent.

C. TabTransformer Model

Referred to the image Fig 1Tab Transformer is designed to learn contextual relationships among structured financial features. Categorical and numerical customer attributes are converted into suitable feature representations. Transformer encoder layers equipped with self-attention then capture interactions among the features **[4]**-**[6]**, **[10]**. The contextual representations are passed to fully connected layers, and a sigmoid output is used to classify a loan application as approved or rejected.

D. Temporal Fusion Transformer Model

Referred to the image TFT processes twelve months of customer financial records to capture long-term temporal dependencies **[3]**. Variable Selection Networks identify informative inputs, Gated Residual Networks support nonlinear feature processing, and temporal self-attention learns relationships across the sequential records. The final decoder and output layers combine the learned temporal and static information to produce the loan approval prediction.

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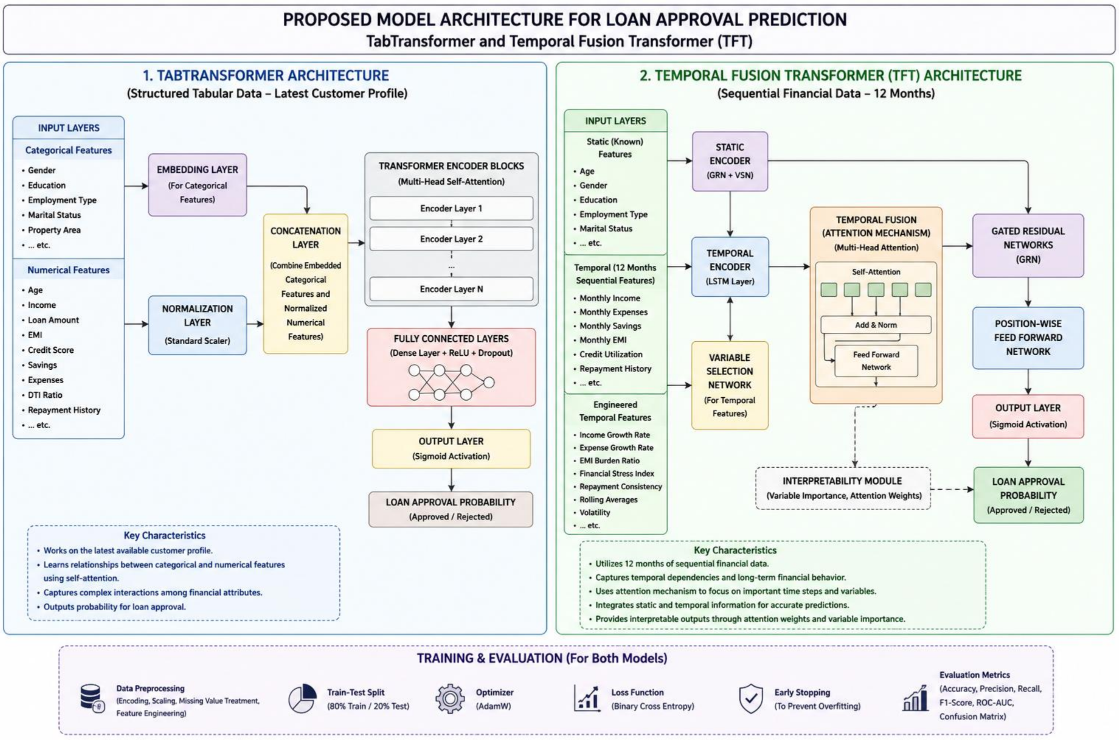

Fig. 1 Model Architectures of TabTransformer and Temporal Fusion Transformer

E. Proposed Comparative Framework

The proposed framework refer to the fig 2 independently trains TabTransformer and TFT from the same enhanced loan approval dataset. TabTransformer models structured customer data through self-attention, while TFT processes twelve months of month-level financial records. Both models use the same missing-value treatment, encoding, scaling and train-test splitting. Accuracy, Precision, Recall, F1-Score, ROC-AUC and confusion-matrix analysis are then computed under comparable experimental conditions. This design enables an objective assessment of the contribution of temporal financial information.

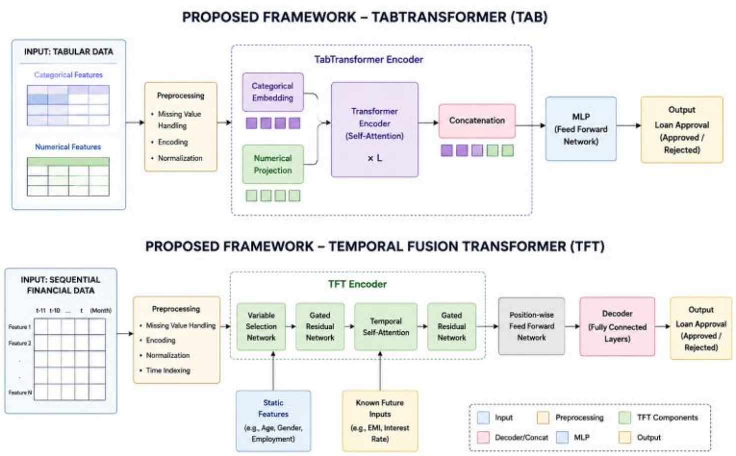

Fig. 2 Proposed Comparative Framework of TabTransformer and TFT

IV. RESULTS AND DISCUSSION

The proposed framework refer to fig 2 was implemented using the PyTorch deep-learning framework and executed on CUDA-enabled GPUs to accelerate model training and inference. Both TabTransformer and TFT were trained using the same enhanced loan approval dataset. Before training, missing values were handled, categorical variables were encoded,

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numerical attributes were normalized and the dataset was divided into training and testing subsets. Both models were optimized using the Adam optimizer with appropriate learning-rate scheduling.

Experimental results show that TabTransformer achieved 93.13% accuracy, whereas TFT obtained 94.75% accuracy. The higher performance of TFT indicates that incorporating temporal financial behaviour can improve loan approval prediction by capturing repayment trends and changes in customer financial patterns over time. The strong performance of both models also demonstrates the suitability of transformer-based architectures for structured and sequential credit-risk data.

A. Evaluation Metrics

Performance is evaluated using Accuracy, Precision, Recall and F1-Score together with ROC-AUC and confusion-matrix analysis. Accuracy measures the proportion of correct predictions, Precision measures the correctness of positive predictions, Recall measures the proportion of actual positive cases identified, and F1-Score provides a harmonic balance between Precision and Recall.

TABLE I EVALUATION METRICS FORMULAS

Accuracy	Precision	Recall	F1-Score
(TP+TN)/(TP+TN+FP+FN)	TP/(TP+FP)	TP/(TP+FN)	2TP/(2TP+FP+FN)

B. Tab Transformer Classification Performance

TABLE II TAB TRANSFORMER CLASSIFICATION REPORT ON TEST DATASET

Class	Precision	Recall	F1-Score	Support
Rejected (0)	0.92	0.91	0.91	320
Approved (1)	0.94	0.95	0.94	480
Accuracy			0.93	800
Macro Avg	0.93	0.93	0.93	800
Weighted Avg	0.93	0.93	0.93	800

The TabTransformer classification report shows balanced performance across rejected and approved applications. The approved class obtains Precision of 0.94, Recall of 0.95 and F1-Score of 0.94, while the rejected class obtains Precision of 0.92, Recall of 0.91 and F1-Score of 0.91. This indicates that contextual modelling of structured customer attributes provides reliable classification performance.

C. Temporal Fusion Transformer Classification Performance

TABLE III TEMPORAL FUSION TRANSFORMER CLASSIFICATION REPORT ON TEST DATASET

Class	Precision	Recall	F1-Score	Support
Rejected (0)	0.95	0.96	0.96	1907
Approved (1)	0.94	0.93	0.93	1271
Accuracy	-	-	0.95	3178
Macro Avg	0.95	0.94	0.95	3178
Weighted Avg	0.95	0.95	0.95	3178

TFT achieves strong classification performance on both classes. For rejected applications, Precision is 0.95, Recall is 0.96 and F1-Score is 0.96. For approved applications, Precision is 0.94, Recall is 0.93 and F1-Score is 0.93. These values support the overall finding that temporal modelling provides additional predictive information.

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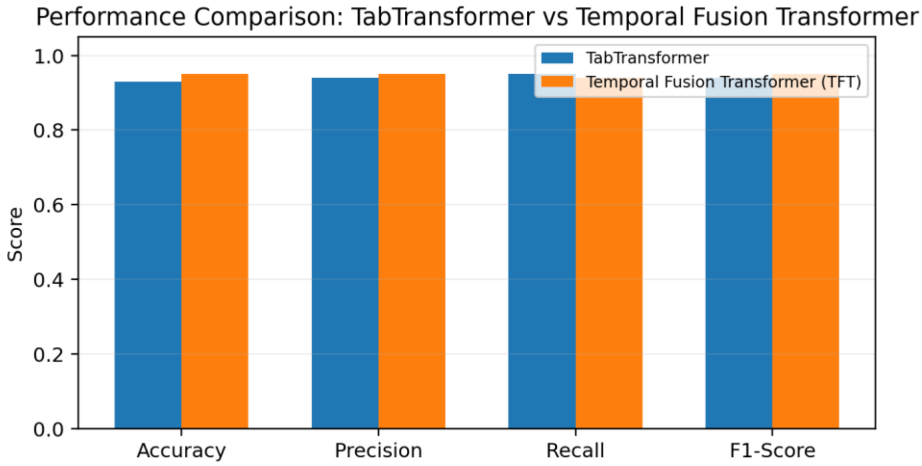

Fig. 3 Performance Comparison of TabTransformer and Temporal Fusion Transformer

Fig. 3 compares Accuracy, Precision, Recall and F1-Score for the two models. The comparison shows strong performance from both transformer architectures, with TFT providing the higher overall accuracy reported in the study.

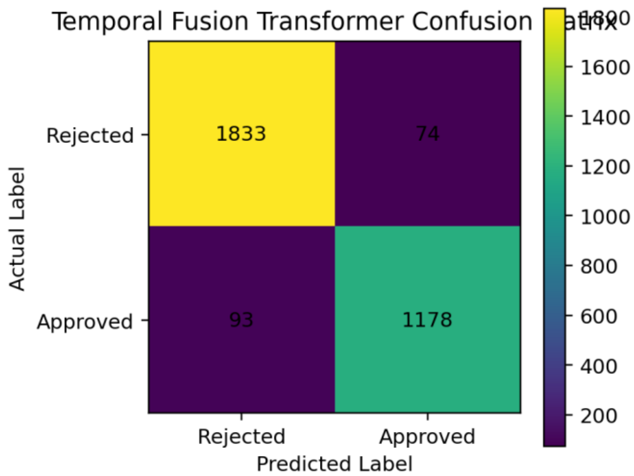

Fig. 4 Confusion Matrix of the Temporal Fusion Transformer

Fig. 4 presents the TFT confusion matrix on the test dataset. The matrix contains 1833 correctly predicted rejected applications, 1178 correctly predicted approved applications, 74 rejected applications predicted as approved, and 93 approved applications predicted as rejected.

D. Comparison with Existing Work

TABLE IV COMPARISON WITH RELATED WORK

Study	Method	Acc.	AUC	Contribution
Jha et al. (2025)	Deep Learning	94%	0.96	Fairness-aware prediction
Hartomo et al. (2025)	TabTransformer	95%	0.98	Explainable credit risk
Li et al. (2025)	Deep Learning	93%	0.95	Loan decision analysis
Raliphada et al. (2026)	Transformer NLP	94%	0.97	Credit risk review
Proposed Framework	TabTransformer + TFT	94.75%	0.9888	Transformer comparison

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The related-work comparison places the proposed framework alongside recent deep-learning and transformer-based studies. The proposed comparison reports 94.75% accuracy and an AUC of 0.9888. Its primary contribution is the direct comparison of TabTransformer and TFT using structured and sequential financial data under consistent experimental conditions.

E. Discussion

The results demonstrate that both transformer architectures are effective for loan approval prediction, but TFT provides higher overall predictive performance. TabTransformer learns contextual relationships among static financial attributes, while TFT uses sequential information to represent changing customer behaviour and repayment trends. The difference between the two models supports the value of temporal financial information for credit-risk assessment.

Several limitations remain. The framework was evaluated using a single enhanced loan approval dataset, and its generalization to financial data from different institutions has not been validated. Macroeconomic indicators such as inflation, interest rates and employment conditions were not incorporated. Future work can evaluate real-world banking datasets, integrate Explainable Artificial Intelligence techniques such as SHAP **[9]**, **[11]**, and add further temporal and macroeconomic indicators to improve accuracy, robustness and fairness.

V. CONCLUSION

This study presented a comparative analysis of TabTransformer and Temporal Fusion Transformer for intelligent loan approval prediction using structured and sequential financial data. Both models were developed and evaluated under identical preprocessing techniques and experimental settings. TabTransformer effectively captures contextual relationships among structured customer financial attributes, while TFT learns temporal patterns from twelve months of historical financial records.

TFT achieved 94.75% accuracy, outperforming TabTransformer at 93.13%, highlighting the importance of temporal financial behaviour in automated lending decisions. Overall, transformer-based architectures provide an accurate and reliable approach for loan approval prediction and credit-risk assessment. Future work will focus on validating the framework with real-world banking datasets, integrating Explainable Artificial Intelligence techniques for transparent decision-making, and incorporating macroeconomic and behavioural indicators.

The results indicate that besides the static attributes, information from a customer's financial history can be useful and not fully represented by their static attributes. Thus, the fused structured financial information and temporal patterns can aid in making more reliable and informed loan approval decisions. This work can be extended by using real world banking data sets to test the models in a real world scenario in the future. Explainable AI methods such as SHAP can also be incorporated to help understand the reasons behind individual predictions. Moreover, if other factors like interest rate, inflation rate, employment situation and other behavioural factors are taken into account, the system would be improved. In conclusion, the study demonstrates the promise of transformer-based models in improving credit risk assessment and loan approval processes through enhanced accuracy, consistency, and intelligence.

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