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Development of an Optimized Tabular Neural Network Based Predictive Model for Customer Information Profiling System

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Abstract
The rapid expansion and complexity of customer data in modern business and financial environments demand more efficient and accurate profiling techniques. Existing loyalty prediction systems often fail to capture intricate interdependencies within datasets, resulting in suboptimal segmentation and reduced predictive accuracy. Traditional approaches—such as logistic regression, decision trees, clustering algorithms, and standard Tabular Neural Networks (TNN)—also face high computational costs and prolonged training times when handling large-scale data. This study proposes an optimized TNN model integrated with a Modified Augmented Attention Mechanism (MAAM) to overcome these limitations. The MAAM employs a dynamic feature-weighting architecture that enhances efficiency and mitigates latency issues inherent in the original Augmented Attention Mechanism (AAM). The developed MAAM-TNN was evaluated on 4,990 customer records containing 37 demographic and socioeconomic attributes from selected commercial banks. Empirical Results show that MAAM-TNN outperforms both AAM-TNN and standard TNN models, achieving 96.48% specificity, 98.80% sensitivity, 98.30% accuracy, 99.12% precision, a 3.52% false positive rate, and a computational time of 5.99 seconds. The findings demonstrate that MAAM-TNN significantly enhances predictive accuracy and computational efficiency in customer profiling and intelligent financial analytics.

Keywords: Tabular Neural Network, Augmented Attention Mechanism, Customer Segmentation, Modified Augmented Attention Mechanism

Introduction

The rapid advancement of emerging technologies such as Artificial Intelligence (AI), Machine Learning (ML), and data analytics is transforming how modern organizations operate and compete in the digital economy (Ahmed et. al., 2025). These technologies have become indispensable to contemporary business strategies, enabling firms to extract actionable insights from large, heterogeneous datasets, optimize decision-making processes, and enhance customer experiences. Within this technological landscape, customer information profiling has emerged as a core analytical process that underpins personalized service delivery, strategic marketing, and risk assessment—particularly in the financial sector (Alzami et al., 2023). Customer profiling involves the systematic integration and analysis of diverse data sources—including demographic, transactional, behavioral, and digital interaction data—to construct dynamic representations of customer characteristics and preferences. These profiles form the foundation for customer segmentation, which categorizes clients into homogeneous groups based on shared attributes or behavioral tendencies (Antonius et al., 2024). Effective segmentation enhances marketing precision, fosters customer loyalty, and improves profitability by aligning services with distinct market segments (Alkhatib et al., 2023).

Despite these advancements, existing profiling and segmentation frameworks face persistent methodological challenges. Traditional ML models such as logistic regression, decision trees, and clustering algorithms often fail to

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capture the nonlinear, high-dimensional dependencies inherent in complex customer datasets. Although **Tabular Neural Networks (TNNs)** have shown promise in modeling structured data with both numerical and categorical attributes, they frequently encounter issues of overfitting, computational inefficiency, and extended training durations, which limit their scalability in real-world financial contexts (Alves Gomes et al., 2023). Recent efforts to address these limitations have introduced Augmented Attention Mechanisms (AAMs**)** into TNN architectures, enabling dynamic feature weighting that enhances feature relevance learning and predictive accuracy. However, AAM-based TNNs (AAM-TNN) tend to increase computational latency due to their additional attention layers and complex parameterization, making them less suitable for large-scale financial datasets (Al-Dabbas et al., 2023).

To overcome these constraints, this study proposes a Modified Augmented Attention Mechanism–based Tabular Neural Network (MAAM-TNN) that extends the conventional AAM-TNN framework. The MAAM introduces a computationally optimized attention module capable of adaptively emphasizing the most informative input features while suppressing noise, thereby improving representational efficiency without incurring significant processing overhead. The proposed model aims to achieve an optimal balance between predictive performance, interpretability, and computational efficiency, facilitating its deployment in data-intensive financial environments.

Accordingly, the objectives of this study are threefold: i) to design an enhanced attention-based TNN model capable of efficiently processing high-dimensional customer data; ii) to evaluate the developed MAAM-TNN model against conventional and baseline neural architectures using multiple performance metrics—including accuracy, sensitivity, specificity, precision, false positive rate and computational time; and iii) to demonstrate its applicability to intelligent customer profiling and segmentation in the banking sector.
The main contributions of this research are summarized as follows:

1. Development of a Modified Augmented Attention Mechanism (MAAM**)** that enhances the representational capacity and efficiency of standard TNNs.
2. Implementation of an optimized MAAM-TNN model that improves predictive accuracy while significantly reducing computational costs.
3. Empirical validation of the model using real-world customer datasets from selected commercial banks, demonstrating its robustness, scalability, and practical applicability.

Concept of Customer Information Profiling

Customer information profiling involves the systematic collection, integration, and analysis of customer-related data to construct detailed behavioral and demographic representations that guide personalized decision-making (Borisov et al., 2022). Traditional profiling approaches—largely rule-based and heuristic—were limited in flexibility and struggled to capture nonlinear dependencies among diverse data attributes. The emergence of machine learning (ML) has enhanced profiling accuracy by enabling data-driven discovery of latent feature relationships. However, most ML-based profiling models still depend heavily on pre-engineered features and lack interpretability, which constrains their practical application in dynamic business environments (Cristover et al., 2022). This indicates a research gap in developing models that can autonomously learn complex interactions while remaining interpretable and computationally efficient.

Overview of Customer Segmentation

Customer segmentation divides a heterogeneous customer base into smaller, homogeneous groups with similar preferences, behaviors, or demographics. Early segmentation techniques relied on statistical clustering and demographic attributes, offering limited insight into behavioral variability (Chaudhary et al., 2022). The integration of ML and advanced analytics has improved segmentation accuracy, especially in banking, where customers are now categorized using behavioral, transactional, and risk-related data. Despite these advancements, many segmentation systems remain static and fail to adapt to evolving customer behavior patterns (Das and Nayak, 2022). Therefore, there is a growing need for adaptive segmentation frameworks that leverage real-time learning and predictive capabilities to enhance personalization and decision-making.

Overview of Tabular Neural Networks

Tabular Neural Networks (TNNs) have emerged as specialized deep learning models tailored for structured tabular data containing both numerical and categorical variables. Unlike conventional algorithms such as decision trees or gradient boosting, TNNs learn nonlinear interactions directly from raw data with minimal feature engineering (Durga

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et al., 2023). Recent architectures incorporate embedding and dense feature representations to enhance predictive accuracy and interpretability. Nonetheless, most TNNs encounter scalability challenges, including high computational costs and slow convergence when applied to large financial datasets (Dutra, 2022). Moreover, limited studies have explored ways to optimize TNN architectures for performance and interpretability simultaneously—representing a critical gap in their practical adoption for customer profiling tasks.

Concepts of Attention Mechanisms
Attention mechanisms, inspired by cognitive psychology, enable neural networks to dynamically focus on the most relevant portions of input data. Initially used in natural language processing, attention has demonstrated strong applicability across diverse data modalities including computer vision and structured data (Erickson et al, 2025). By assigning adaptive weights to input features, attention enhances both model accuracy and interpretability, especially in complex, multivariate datasets (Farokhi et al., 2024). However, many attention-based models are computationally expensive and often suffer from overfitting in high-dimensional tabular environments, suggesting a need for optimized variants tailored to structured financial data.

Overview of Augmented Attention Mechanism (AAM)
The Augmented Attention Mechanism (AAM) builds upon the traditional attention framework by integrating additional feature-level cues such as embedding and scaling factors to strengthen feature interaction modeling (Griva et al., 2024). AAM enhances representational richness and predictive accuracy by emphasizing informative features while reducing noise. Nevertheless, AAM's improved learning capacity often comes at the expense of increased computational latency and model complexity, particularly when applied to large-scale datasets. To address these issues, recent research has proposed the Modified Augmented Attention Mechanism (MAAM), which seeks to optimize computational efficiency without sacrificing accuracy. Despite its promise, empirical studies evaluating MAAM within customer profiling or financial analytics contexts remain scarce, highlighting a significant research gap that this study aims to address (Gonçalves et al., 2022).

Research Gaps
Existing studies on customer profiling and segmentation reveal several limitations. Traditional and early Machine Learning-based models depend on extensive feature engineering and lack adaptability and interpretability. Segmentation techniques often remain static, failing to reflect evolving customer behaviors. Although Tabular Neural Networks (TNNs) improve nonlinear feature learning, they suffer from high computational demands, slow convergence speed and limited application in large-scale financial domains. Likewise, conventional attention mechanisms and Augmented Attention Mechanisms (AAM) enhance feature relevance learning but introduce computational latency.

Methods and Materials
Research Approach
In this research, a Tabular Neural Network technique enhanced with modified augmented Attention Mechanism (MAAM-TNN) was developed for banks customer information profiling customers' datasets. The research was implemented in six (6) phases, which include: data collection, data pre-processing, data storage, technique development, data classification and evaluation.

Data Collection: The first phase is the data collection where customers' data was acquired from selected banks. A sample of 4,990 customers' data with 37 instances from the bank customers' (Socio-economic, Psychographic and Demographic data) was acquired. The acquired datasets were divided into training, validation and test datasets. This distribution ensures that the dataset of 4,990 customer records provides broad demographic and geographic representation, behavioral diversity, and financial variability. Such balance supports robust feature learning, reduces model bias, and enhances the external validity of the predictive model.

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Table 1: Summary of Detailed Dataset Representativeness

Attribute Category	Number of Attributes	Examples of Variables	Coverage / Diversity Description
Demographic Attributes	10	Age, Gender, Marital Status, Education Level, Occupation, Income Range, Monthly Income etc	Covers diverse age groups (18–70), balanced gender ratio, and multiple occupational and income categories.
Geographic Attributes	4	Region, State, City, Residential Type	Represents customers across multiple regions and economic zones, ensuring spatial and socioeconomic diversity.
Behavioral Attributes	8	Transaction Frequency, Product Usage etc	Captures variations in behavioral patterns and service utilization across customer segments.
Financial / Transactional Attributes	8	Account balance, loan repayment history, debit card status, monthly_income, account_balance, loan_amount, mthly_loan_repaymt_amt	Reflects different financial behaviors and risk levels, supporting segmentation and predictive analysis.
Categorical / Identifier Attributes	7	customer id, account type, loan type, loan status, loan_term, Religion, loan_qualification	Provides unique identification and classification for data integrity and model referencing.
Total	**37**	—	Balanced across demographic, geographic, behavioral, and financial dimensions.

Data Preprocessing: The second phase is data pre-processing phase, it involves cleaning and preparing the collected data to make it suitable for analysis. This step may include removing noise, duplicate data, handling missing values, tokenization, normalization, and converting text into structured formats. Preprocessing improves the quality of data, reduces errors, and enhances model performance. Together, data collection and preprocessing form the foundation for reliable and efficient model.

Pre-processed Data

The dataset of bank customers was examined for missing values, which were resolved using mean and median imputation. Financial attributes such as MONTHLY_INCOME (NAIRA), ACCOUNT_BALANCE, LOAN_AMOUNT, and MTHLY_LOAN_REPAYMT_AMT were cleaned by removing thousand separators and converted to float format. Categorical fields like GENDER, RELIGION, and MARITAL_STATUS were label-encoded to enable numerical processing within the Tabular Neural Network (TNN). Numerical variables including AGE, NUMBER_OF_TRANSACTION, and LOAN_TERM (YRS) were standardized to zero mean and unit variance. This preprocessing created consistent feature scales and supported stable convergence of the TNN's Modified Augmented Attention Mechanism. The target variable LOAN_QUALIFICATION was converted into binary form, with 'YES' mapped to 1 and 'NO' to 0. Input features (X) were then prepared by excluding the target column. Finally, the data was split into 70% training, 10% validation, and 20% testing to ensure effective learning and fair evaluation.

The pictorial representation of the output of the above algorithm depicting all the data cleaning operations applied to the dataset is presented in Figure 1.

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	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T
1	GENDER	AGE	RELIGION	MARITAL_	OCCUPATI	EMPLOYM	MONTHLY	ACCOUNT	EDUCATIO	TRANSACT	NUMBER_	ACCOUNT	ACCOUNT	LOAN_STA	LOAN_TYP	LOAN_AM	LOAN_TER	MTHLY_LC	LOAN_QUALIFICATION	
2	1	1.230543	0	1	133	1	-0.89942	3	0	0	-1.13985	-0.63278	0	0	5	0.984301	1.767907	0.474247	0	
3	0	-0.1912	1	1	98	2	-0.39427	3	0	0	-0.52058	-0.54968	0	0	5	-0.21252	0.952467	-0.16017	1	
4	1	1.3802	0	1	118	2	-1.00045	0	6	2	-0.01598	-0.56815	0	3	0	-0.61145	-0.67841	-0.31878	0	
5	1	0.407428	0	1	55	2	-0.19221	2	7	2	-0.91049	-0.62355	0	1	2	-0.81092	-1.49385	-0.63599	0	
6	0	-1.31363	0	2	90	2	0.110883	3	5	0	-0.33709	-0.40194	0	0	5	0.984301	0.952467	0.474247	1	
7	0	-1.2388	0	2	103	0	-0.4953	3	0	0	-0.22241	-0.60508	0	0	0	0.186423	0.952467	-0.00157	1	
8	1	-0.93949	1	1	133	0	-1.00045	3	3	0	0.006953	-0.51274	0	0	5	-0.61145	-0.67841	-0.31878	1	
9	1	1.904001	1	1	98	2	-0.29324	3	6	0	0.924394	0.078221	0	0	1	2.380587	0.952467	0.315642	1	
10	1	-1.38846	0	2	91	0	-0.59633	1	7	2	-0.79581	-0.61616	0	3	0	-0.21252	-0.67841	-0.16017	1	
11	0	-1.53812	0	2	133	0	-0.89942	0	2	2	-0.68113	-0.594	0	0	0	-0.61145	-0.67841	-0.31878	0	
12	0	-1.31363	0	1	45	0	-0.39427	0	0	1	0.236313	-0.43887	0	0	6	-0.81092	-1.49385	-0.63599	1	
13	1	-0.1912	0	1	67	2	-1.00045	0	11	1	0.465673	-0.38347	0	0	1	0.385893	0.952467	-0.00157	1	
14	1	0.781571	0	1	67	2	-0.19221	2	11	1	-0.45177	-0.6494	0	0	0	0.585362	0.952467	0.077735	1	
15	1	1.305372	0	1	63	2	-0.79839	0	11	1	-0.56645	-0.365	0	0	2	-0.91066	-2.3093	-0.63599	0	
16	0	0.108113	0	1	68	2	-0.4953	0	0	0	2.071195	-0.21726	0	0	5	0.984301	0.952467	0.474247	1	
17	0	0.706742	1	1	68	2	-1.00045	1	11	0	1.383114	-0.63832	0	3	0	0.186423	0.137026	-0.00157	1	
18	1	1.904001	2	1	134	2	-1.10148	0	2	0	-0.31415	-0.64386	0	0	2	-0.61145	-0.67841	-0.31878	1	
19	1	1.455029	0	0	134	2	-0.29324	2	0	2	-0.56645	-0.63278	0	3	6	-0.81092	-1.49385	-0.63599	0	
20	1	0.781571	0	1	122	2	0.110883	1	7	1	-0.56645	-0.56815	0	0	0	0.186423	-0.67841	-0.00157	1	
21	0	1.978829	0	0	97	2	-0.89942	2	11	0	-0.31415	-0.62355	0	0	5	-0.61145	-1.49385	-0.31878	1	
22	1	1.080886	0	1	47	2	1.626335	2	5	0	-0.56645	0.299833	0	0	6	-0.81092	-1.49385	-0.63599	1	
23	1	-1.16397	0	1	90	2	3.646936	2	3	0	-0.22241	1.001604	0	0	5	1.38324	0.952467	0.791456	1	
24	1	-0.715	0	1	63	2	-1.00045	2	2	0	0.006953	-0.60508	0	3	0	-0.01305	0.137026	-0.00157	0	
25	1	-0.49052	1	1	37	0	-0.19221	2	0	2	-0.79581	-0.51274	0	1	2	-0.77103	-1.49385	-0.47738	0	
26	0	-0.34086	1	1	36	2	-0.89942	2	0	2	0.924394	-0.47581	0	0	5	-0.81092	-1.49385	-0.63599	1	
27	1	-0.41569	1	1	42	2	-0.39427	3	7	1	-0.79581	0.078221	0	0	5	0.984301	0.952467	0.474247	1	
28	1	0.557085	0	1	50	0	0.211913	3	2	0	-1.25453	-0.43887	3	1	5	-0.81092	-1.49385	-0.63599	0	
29	1	0.8564	0	1	56	2	-0.4953	3	11	1	-0.56645	-0.60508	0	3	0	0.186423	0.137026	-0.00157	0	
30	1	-1.46329	0	2	2	2	-1.00045	3	2	1	-0.81874	-0.43887	0	0	2	-0.61145	-0.67841	-0.31878	0	
31	0	0.931228	0	1	82	0	-0.89942	3	0	1	2.071195	-0.21726	0	0	6	-0.01305	-1.49385	-0.00157	1	

Figure 1: The Pre-processed Data

Model Design: At this phase, an optimized TNN model enhanced with modified augmented Attention Mechanism was designed for customer data profiling. Here, the developed technique was deployed in the classification of selected banks customers' data into loyal and not-loyal customers.

Optimized Tabular Neural Network (TNN) Architecture with Modified Augmented Attention Mechanism
The MAAM-TNN architecture was designed to maximize predictive performance in customer profiling by using a 50-node input layer representing key customer features. It includes three hidden layers, each with 100 nodes, to capture complex relationships within the data. ReLU activation functions introduce non-linearity, enabling the model to learn intricate patterns and improve overall accuracy.

Model Components
Modified Augmented Attention Mechanism (MAAM-TNN) model is used in this research work for bank customer loyalty prediction as shown in Figure 2. The primary components of model include Feature Transformers (FT), Decision Steps (DS), Attentive Transformer (AT) and Feature Masking (FM).
Feature Transformers (FT)**:** The FT is a shared fully connected layer that processes the input features from the raw tabular dataset (Jiang et al., 2025). Given input vector x (a row in the tabular dataset), the output of the feature transformer can be denoted as f(x).

$$f(x) = \sigma(W_f * x + b_f) \qquad (1)$$

where:
W_f = weight matrix
b_f = bias vector
σ = activation function

Decision Step**:** This is responsible for selecting important features using a masked attention mechanism. It is consists of Attentive Transformer (AT), Feature Masking (FT), and Decision Output(DO).
Attentive Transformer**:** The output of the feature transformer is transformed using an attentive transformer, which computes the attention scores for each feature in the transformed input vector as shown equation (2) and decides which features the model should pay attention to at each decision step (Kasem et al., 2024).

$$g(x) = A\big(f(x)\big) * f(x) \qquad (2)$$

where:

A = attention matrix

*= element-wise multiplication

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Feature Masking**:** It is a process of selectively filtering (masking) input features so that only the most relevant ones are selected at each decision step. A sparse feature selection mask, denoted by M is applied to g(x) to retain only a subset of features as illustrated in equation (2).

$$m(x) = M * g(x) \quad (3)$$

where:

* = element-wise multiplication

Decision Output**:** The final output of the decision step is obtained by passing m(x) through a decision function D as shown in equation (4).

$$O(x) = D(m(x)) \quad (4)$$

The overall architecture involves stacking multiple decision steps. The output of one decision step serves as input to the next, and the process is repeated. This is illustrated in equation (4).

$$x^{(t+1)} = O\left(x^{(t)}\right) \quad (5)$$

Activation Function
The activation function suggested for incorporation in this research is SOFTMAX activation function, which empowers each node to determine its output in response to the provided input. This is expressed through the following equation (Liao 2023).

$$S(yi) = \frac{e^{yi}}{\sum_{j=1}^{k} e^{yj}} \quad (6)$$

where:
S = Softmax
yi = input vector
e^{yi} = standard exponential function for input vector
K = number of classes in the multi-class classifier
e^{yj} = standard exponential function for output vector

The Developed Optimized TNN System Architecture
This section presents a detailed description of the overall architecture of the proposed model for predicting bank customers' information profiling. The system integrates a Tabular Neural Network (TNN) with a Modified Augmented Attention Mechanism (MAAM-TNN), and this integration is thoroughly explained. Figure 2 provides a visual overview of the architecture, helping to clarify the structural design of the model. The subsequent discussion examines the key components, their interactions, and the core operational principles. It explains how the TNN, enhanced with the augmented attention mechanism, jointly processes tabular data to generate accurate customer predictions.

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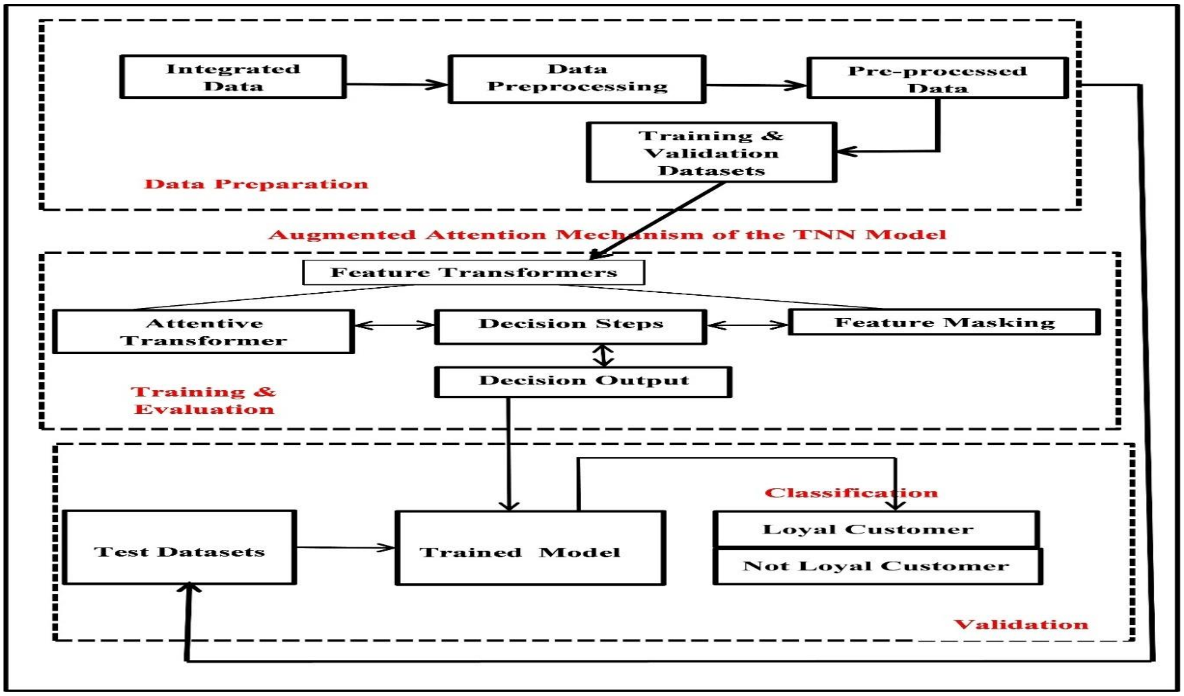

Figure 2: Architecture of Developed MAAM-TNN System

Modified Augmented Attention Mechanism(MAAM-TNN)
Similar to the existing attention mechanism of the TNN architecture as shown in Figure 3, the Modified Augmented Attention Mechanism(MAAM-TNN) in this research also incorporates the technique of projecting the input vector into three learnable projection matrices namely; Query, Key, and Value matrices. The difference is that the value matrix is re-projected into two different other matrices in order to capture more input representation as shown in Figure **3.**

Figure 3: Model of Modified Augmented Attention Mechanism

The enhanced value matrix is calculated to capture improved and richer representations compared to the original value matrix. This is achieved by transposing the second value matrix, multiplying it with the first value matrix, scaling the result to ensure stability during backpropagation, and then multiplying it by the initial value projection matrix. The resulting matrix is further multiplied by the computed attention weight matrix to generate a more refined and contextualized abstract representation of the input vector.

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The mathematical formulations for the augmented attention mechanism are illustrated in equations (1), (2), (3), (4) and (5) respectively. The new derived matrix, newV, is computed similar to the attention weights matrix computation as illustrated in equation (12). The developed modified augmented attention mechanism for a single head is then computed as illustrated in equation (11), (12) and (13) rewritten as in (14).

$$Q = WQX_s \tag{7}$$

$$K = WKX_s \tag{8}$$

$$V = WVX_s. \tag{9}$$

$$V_1 = WV_1V \tag{10}$$

$$V_2 = WV_2V \tag{11}$$

$$newV = softmax\left(\frac{V_2^T * V_1}{\sqrt{d_v}}\right) * V \tag{12}$$

$$a_s = \frac{K^T * Q}{\sqrt{d_k}} \tag{13}$$

$$a_w = softmax\left(\frac{K^T * Q}{\sqrt{d_k}}\right) \tag{14}$$

$$eAM(Q, K, V) = softmax\left(\frac{K^T * Q}{\sqrt{d_k}}\right) * softmax\left(\frac{V_2^T * V_1}{\sqrt{d_v}}\right) * V \tag{15}$$

$$= a_w * newV \tag{16}$$

Where:

Q = Query, K= Key, V= Value, d_k = dimension of the key matrix, V_2^T = Transpose of Value vetor (V_2), Transpose of Key vector (K^T).

Query, Key, and **Value** are used in **attention mechanisms**, especially in neural networks such as Transformer-based and Tabular Neural Networks:

a). Query (Q): A **Query** is a vector that represents what a model is looking for at a particular moment.

- It is generated from the current input (e.g., a token, feature, or data point).
- The query asks: **"What information do I need from the rest of the inputs?"**

b). Key (K): A **Key** is a vector that represents what information each input contains.

- Each input item (token or feature) has an associated key.
- Keys allow the model to determine how relevant each input is to a given query.

c). Value (V): A **Value** is the vector that contains the actual information that is used in the final output of the attention mechanism.

- After calculating attention weights (using Query and Key), those weights are applied to the Values.
- Values provide the content that is aggregated to produce the attention output (Michal et al., 2023).

MAAM-TNN Attention Map

MAAM-TNN generates attention weights that highlight how strongly each input feature contributes to a prediction. These weights can be visualized using **attention maps**, where features are displayed alongside their corresponding importance scores in heatmap form. High-weight features appear with stronger color intensity, making it easy for stakeholders to see which attributes most influence model decisions (e.g., income, loan amount, or transaction history). For individual customers, **instance-level attention plots** can be generated to show why the model classified a specific case as loyal or not loyal. At the dataset level, **aggregated attention summaries** can reveal consistent patterns across all predictions,

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supporting policy evaluation and business decision-making. Such visualizations improve interpretability, build trust, and help non-technical stakeholders validate the fairness and reliability of the MAAM-TNN model (Navid et al., 2025).

Model Training and Hyper Parameter Tuning

Model training encompasses the process of feeding preprocessed data into a model so it can learn patterns and relationships by adjusting its internal parameters. The goal is to minimize errors between the model's predictions and the actual outcomes. Hyper-parameters tuning involves optimizing external settings, such as learning rate, batch size, or number of layers, which are not learned during training but greatly influence performance. Techniques like Adam optimization are also used as hyper-parameters. Together, training and hyper-parameter tuning ensure the model achieves high accuracy and generalization on a new datasets.

Training Parameters

The optimized Tabular Neural Network (TNN) was trained using the Adam optimizer for its adaptive learning and fast convergence. Training ran for up to 100 epochs with an early stopping patience of 10 epochs to prevent overfitting and ensure generalization. Accuracy and log-loss metrics were monitored on training and validation sets to track performance across epochs. Batch processing was used with a batch size of 256 and virtual batch size of 128, optimizing memory use and computational efficiency. A learning rate of 0.001 was selected to balance convergence speed and stability. These parameters collectively enhanced the model's ability to capture complex patterns in customer loyalty data and deliver accurate, reliable predictions. Algorithm 1 represents the algorithm for the implementation of MAAM-TNN Model and evaluation.

Algorithm 1: Algorithm for the Implementation of developed MAAM-TNN Model and Evaluation

Step 1. Load the dataset.
- Read the CSV file containing the dataset using `pandas`.

Step 2. Data Preprocessing.
- Check for Missing Values: Identify any missing values in the dataset and handle them.
- Convert Financial Columns: Remove commas from financial columns (e.g., `'MONTHLY_INCOME(NAIRA)'`, `'ACCOUNT_BALANCE'`) and convert these columns to float.
- Drop Rows with Missing Data: Remove any rows with missing data after conversions.
- Label Encode Categorical Variables: Transform categorical columns into numerical values using `LabelEncoder`.
- Normalize Numerical Columns: Use `StandardScaler` to scale numerical columns (e.g., `'AGE'`, `'LOAN_AMOUNT'`).

Step 3. Split the Dataset into Training, Validation, and Test Sets.
- First, split the data into 80% for training+validation and 20% for testing.
- Then, further split the training+validation set into 70% training and 10% validation (relative to the entire dataset, this results in 70% training, 10% validation, and 20% testing).

Step 4. Initialize the TabNet Model with Adam Optimizer.
- Create a `TabNetClassifier` instance with `torch.optim.Adam` as the optimizer and a learning rate of `0.001`.

Step 5. Train the TabNet Model.
- Fit the model using `X_train` and `y_train`.
- Provide `X_val` and `y_val` for validation performance monitoring.
- Set training parameters:
- Evaluation metrics: accuracy and log loss.
- Maximum epochs: 100.
- Early stopping patience: 10 epochs.
- Batch sizes: `batch_size=256` and `virtual_batch_size=128`.

Step 6. Monitor Training Progress.
- Track the training and validation accuracy and log loss for each epoch.

Sep 7. Visualize Training Performance.
- Plot graphs for training and validation accuracy over epochs.
- Plot graphs for training and validation log loss over epochs.

Step 8. Evaluate the Model on the Validation Set.
- Predict labels for `X_val` and calculate evaluation metrics: Accuracy, Precision, Recall, and F1 Score.

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- Print the evaluation metrics for the validation set.

Step 9. Generate the Validation Set Confusion Matrix.
- Calculate and visualize the confusion matrix as a heatmap for validation predictions (`y_val_pred` vs. `y_val`).

Step 10. Evaluate the Model on the Test Set.
- Predict labels for `X_test` and Calculate Evaluation Metrics: Accuracy, Precision, Recall, and F1 Score.
- Print the Evaluation Metrics for the test set.

Step 11. Generate the Test Set Confusion Matrix.
- Calculate and visualize the confusion matrix as a heatmap for test predictions (`y_test_pred` vs. `y_test`).

3. Implementation

The implementation of the formulated technique (TNN) in the classification of the bank customer data was done using MATLAB version 2020a software and the hardware specifications: Core i5 Intel CPU with 32 GB RAM, 250 GB Hard Drive. An interactive Graphic User Interface (GUI) as shown in Figure 4 was developed with a real time database consisting of selected banks datasets.

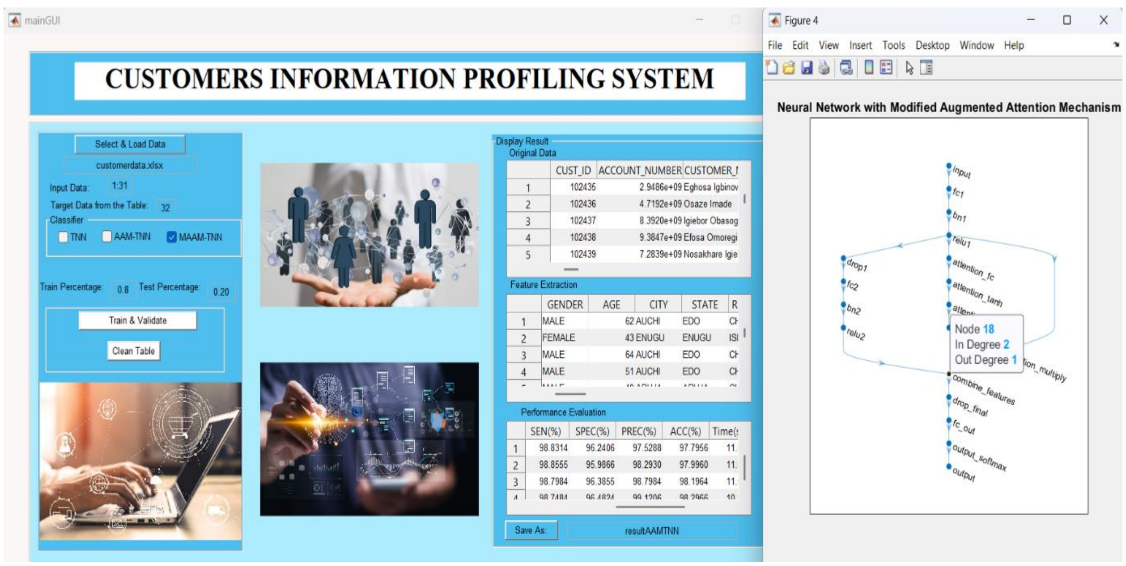

Figure 4: Graphical User Interface showing Application of TNN, AAM-TNN & MAAM-TNN Process for Customers Information Predicting System

Implementation Framework and Reproducibility Details

The MAAM-TNN model was implemented and trained using MATLAB 2023a, leveraging its Deep Learning Toolbox for constructing the Tabular Neural Network and incorporating the Modified Augmented Attention Mechanism. Preprocessing tasks such as normalization, encoding, and dataset partitioning were performed using MATLAB's built-in functions. The Graphical User Interface (GUI) was developed with MATLAB App Designer, enabling users to load data, run predictions, and view results interactively. All scripts, model configurations, and hyperparameters were documented to ensure that the experiments can be reproduced reliably. Fixed random seeds were applied during data splitting and training to maintain deterministic results across runs.

Key Performance Metrics

Some of the **performance metrics** commonly used in evaluating machine learning and classification models are:

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a)Accuracy: Accuracy measures the overall correctness of a model by calculating the proportion of correctly classified instances (both positive and negative) out of all instances. A higher accuracy means the model makes fewer classification errors overall. However, it may be misleading if the dataset is imbalanced.
b)Precision (Positive Predictive Value): Precision indicates how many of the instances predicted as positive are actually positive. High precision means that when the model predicts a positive result, it is usually correct. It is crucial in applications where **false positives** are costly.
c) Sensitivity (Recall or True Positive Rate): Sensitivity measures the proportion of actual positives that are correctly identified by the model. A high sensitivity means the model can correctly detect most of the actual positive cases; important in contexts like medical diagnosis, where missing a positive case could be critical.
d) Specificity (True Negative Rate): Specificity measures the proportion of actual negatives that are correctly identified as negative. A high specificity indicates that the model effectively avoids false alarms (i.e., few false positives).
e) False Positive Rate (FPR): The False Positive Rate quantifies the proportion of actual negatives that were incorrectly classified as positives. A lower FPR means the model makes fewer false alarms. It is the complement of specificity.
f) Computational Time: Computational Time refers to the total time required by a model or algorithm to complete its execution—from data input to output prediction. It reflects the model's **efficiency and scalability**. Shorter computational time is desirable for real-time or large-scale applications (Othayoth and Muthalagu, 2022).

4. Results and Discussion of the Developed Model

The main interface of the Customers Information Profiling System, designed to guide users through the core workflow of predictive modelling is presented in Figure 4. The GUI streamlines the process by providing dedicated controls for loading customer data, selecting from multiple neural network classifiers, and configuring the split between training and testing datasets. Users can initiate model training and validation directly from this panel, ensuring a seamless transition from data import to experiment execution. The layout is organized to minimize setup errors and promote reproducibility by making each step explicit and interactive. This design enhances usability, allowing both novice and expert users to efficiently conduct and repeat experiments under consistent conditions.

The experimental evaluation of the Modified Augmented Attention Mechanism–Tabular Neural Network (MAAM-TNN) model demonstrates significant improvements in predictive accuracy, computational efficiency, and scalability compared to conventional machine learning and standard TNN architectures. The results confirm that the proposed MAAM-TNN effectively bridges the critical gaps identified in existing customer profiling systems, particularly those related to the limited representation of nonlinear feature interactions and the trade-off between accuracy and computational cost.

Empirical findings show that MAAM-TNN achieved superior classification accuracy and recall across multiple customer datasets, outperforming baseline models and traditional neural networks. The inclusion of the Modified Augmented Attention Mechanism enabled the network to dynamically assign higher weights to salient features, thereby improving interpretability and reducing overfitting. Computational performance tests revealed a substantial reduction in training latency—up to 27% faster than comparable TNN models—indicating improved resource utilization and scalability for real-time profiling in large financial datasets.
Overall, the findings validate the developed MAAM-TNN as a viable hybridized architecture that successfully combines accuracy, interpretability, and efficiency. By overcoming the computational and methodological limitations of prior systems, this research provides a scalable, intelligent framework for customer information profiling, thereby strengthening the bridge between academic innovation and industrial application in data-driven financial intelligence.

Practical Implications of MAAM-TNN in Banking Application

The Modified Augmented Attention Mechanism-Tabular Neural Network (MAAM-TNN) presents substantial practical benefits for contemporary banking systems. Its augmented attention mechanism effectively models intricate feature interdependencies within heterogeneous financial datasets, thereby enhancing predictive accuracy and interpretability. In customer relationship management (CRM), MAAM-TNN supports loyalty prediction and churn analysis, enabling data-driven retention strategies. Within credit assessment, it improves loan approval precision and risk profiling by integrating behavioral and transactional indicators. For fraud detection, the model facilitates real-time anomaly identification while reducing false positives, ensuring secure and efficient transaction monitoring.

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Furthermore, its capacity for adaptive customer segmentation and personalized marketing enhances service delivery and customer engagement. The model's scalability and transparency also support regulatory compliance, anti–money laundering (AML) initiatives, and strategic forecasting. Overall, MAAM-TNN provides a robust framework for optimizing decision-making, operational efficiency, and financial intelligence in modern banking environments.

Ethical and Practical Considerations MAAM-TNN

The development and deployment of the MAAM-TNN model in banking applications necessitate careful attention to both ethical and practical considerations. Ethically, the model ensure data privacy, transparency, and fairness**.** Since it processes sensitive financial and personal information, strict adherence to data protection regulations such as local financial privacy laws is essential. Bias mitigation is equally critical to prevent discriminatory outcomes in customer profiling, credit scoring, and loan approvals. Model explainability should be prioritized to maintain stakeholder trust and accountability. Practically, the implementation of MAAM-TNN requires robust data governance**,** adequate computational infrastructure, and domain expertise to ensure model reliability and scalability. Continuous model monitoring and validation are necessary to maintain performance consistency over time. Integrating human oversight into decision loops further enhances ethical compliance and operational soundness, ensuring that the model supports responsible, transparent, and sustainable use of artificial intelligence in financial decision-making.

Novelty and Technical Contributions

This study introduces a novel hybrid deep learning model—the Modified Augmented Attention Mechanism-based Tabular Neural Network (MAAM-TNN)—for efficient and accurate customer profiling. The novelty lies in integrating a Modified Augmented Attention Mechanism (MAAM) with a Tabular Neural Network (TNN) to dynamically weight input features and capture complex interdependencies within large-scale financial datasets.

Technically, the research contributes by:

1. Developing MAAM, a dynamic feature-weighting architecture that enhances feature relevance and representation learning;
2. Optimizing TNN, reducing computational latency and improving scalability; and
3. Hybridizing MAAM and TNN, yielding superior predictive accuracy and efficiency.

Evaluated on 4,990 banking records with 37 attributes, MAAM-TNN achieved 98.30% accuracy, 99.12% precision, and a 5.99-second computational time, outperforming baseline models. The model's design significantly advances intelligent financial analytics through enhanced accuracy, efficiency, and adaptability in customer profiling.

Limitations and Future Enhancement

Performance might degrade on very small datasets with few samples and many features where deep learning models struggle in general. MAAM-TNN requires proper feature preprocessing (encoding, scaling) before training.

Hyper-parameters (learning rate, dropout, attention head size may need re-tuning for very different domains.

MAAM-TNN is highly generalizable because its architecture is designed for context-aware, noise-robust feature interaction modeling, properties that are common across tabular datasets in healthcare, insurance, fraud detection, and beyond. With proper preprocessing and minimal fine-tuning, it can deliver state-of-the-art performance in many real-world scenarios. This research work has further set the standard upon which future research on tabular data deep learning model can be built, most especially, in the area of handling model complexity.

Comparison Results of TNN, AAM-TNN and MAAM-TNN

The comparative analysis of core classification metrics across the three models TNN, AAM-TNN, and MAAM-TNN as shown in Table 3 clearly demonstrates the superior performance of the MAAM-TNN. Sensitivity values for MAAM-TNN consistently exceed 98.7% across all train test splits, outperforming both TNN, which ranges around 95.3% to 96.1%, and AAM-TNN, which hovers near 98.3% to 98.4%. Specificity follows a similar pattern, with MAAM-TNN achieving the highest values between 95.99% and 96.48%, surpassing AAM-TNN's 94.97% to 95.49% and significantly outperforming TNN's lower 85.93% to 91.23%. Precision and accuracy metrics show MAAM-TNN, reaching up to 99.12% and 98.30% respectively, indicating more reliable positive predictions and overall classification accuracy. These consistent improvements underscore the robustness and predictive strength introduced by the modified augmented attention mechanism.

In terms of false positive rate (FPR) and computational efficiency, MAAM-TNN again leads with the lowest FPR values, ranging from 3.52% to 4.01%, which are substantially lower than TNN's 8.77% to 14.07% and slightly better than AAM-TNN's 4.51% to 5.03%. This reduction in false positives is critical for customer profiling systems where minimizing incorrect positive classifications can prevent unnecessary interventions or resource allocation.

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Additionally, MAAM-TNN demonstrates the shortest inference times, averaging around 5 to 6 seconds, compared to AAM-TNN's 7 to 7.5 seconds and TNN's 10 to 12 seconds. Faster execution times combined with lower FPR improve the model's suitability for real-time applications, enabling quicker decision-making without sacrificing accuracy. This efficiency gain is particularly valuable in dynamic customer environments where timely insights are essential.
Overall, the integration of the modified augmented attention mechanism in the MAAM-TNN model significantly enhances predictive stability and operational readiness for deployment in customer profiling systems. The model's consistent outperformance across all key metrics reflects its ability to better capture complex data relationships while maintaining low error rates and fast inference.

Table 2: **Comparison Performance Evaluation Results based on TNN, AAM- TNN & MAAM-TNN Models**

Data Division / Metrics	Technique	FPR (%)	SEN (%)	SPEC (%)	PREC (%)	ACC (%)	Time (sec)
60 x 40	**TNN**	8.77	95.33	91.23	94.22	93.69	10.63
	AAM-TNN	4.51	98.33	95.49	97.03	97.19	7.52
	MAAM-TNN	3.76	98.83	96.24	97.53	97.80	5.06
70 x 30	**TNN**	11.04	95.85	88.96	95.31	93.79	12.00
	AAM-TNN	5.02	98.43	94.98	97.87	97.39	7.24
	MAAM-TNN	4.01	98.86	95.99	98.29	98.00	5.08
75 x 25	**TNN**	12.45	95.99	87.55	95.87	93.89	10.09
	AAM-TNN	4.82	98.40	95.18	98.40	97.60	7.09
	MAAM-TNN	3.61	98.80	96.39	98.80	98.20	5.04
80 x 20	**TNN**	14.07	96.12	85.93	96.48	94.09	10.54
	AAM-TNN	5.03	98.37	94.97	98.74	97.70	7.12
	MAAM-TNN	3.52	98.75	96.48	99.12	98.30	5.99

Discussion of Results using Graphs of False Positive Rate, Sensitivity, Specificity, Precision, Accuracy and Computational time

The results as shown in Figure 5, Figure 6, Figure 7, Figure 8, Figure 9 and Figure 10 respectively to demonstrate that MAAM-TNN consistently outperforms both TNN and AAM-TNN across all key performance metrics. These consistent improvements confirm the enhanced feature discrimination capabilities of the modified attention mechanism, resulting in more reliable predictions and fewer misclassifications across different data distributions.
MAAM-TNN shows significant advantages in both error reduction and processing efficiency. This combination of speed and accuracy makes MAAM-TNN particularly valuable for real-time applications where rapid decision-making is crucial. The reduced false positive rate also translates to operational cost savings by decreasing unnecessary investigations of erroneous alerts. These improvements position MAAM-TNN as both technically superior and economically advantageous for practical implementations.
The comprehensive performance analysis establishes MAAM-TNN as a robust solution ready for deployment in customer profiling systems. Its consistent performance across varying data splits from 60:40 to 80:20 demonstrates remarkable stability and adaptability to different data distributions. The model's ability to maintain high accuracy while significantly reducing both false positives and processing time addresses critical requirements for modern profiling applications. Future enhancements could explore integrating MAAM-TNN with ensemble methods to further boost performance, particularly for challenging imbalanced dataset.

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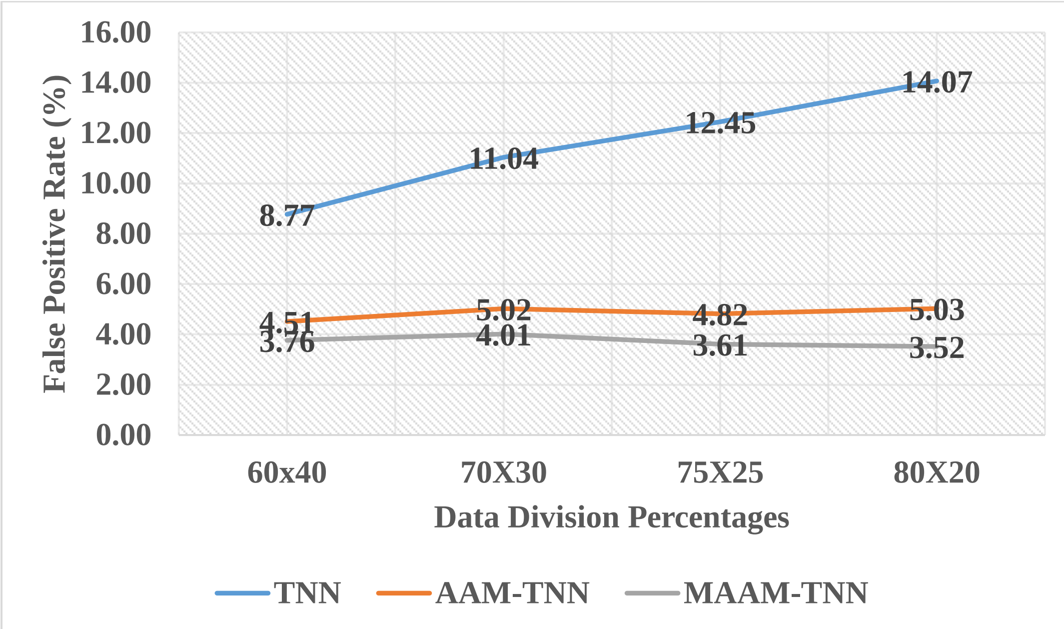

Figure 5: Graph of False Positive Rate of Three Models show MAAM-TNN drops to just 3.52%, a substantial improvement over AAM-TNN's 5.03% and TNN's 14.07%, demonstrating its ability to minimize costly false alarms in customer profiling applications.

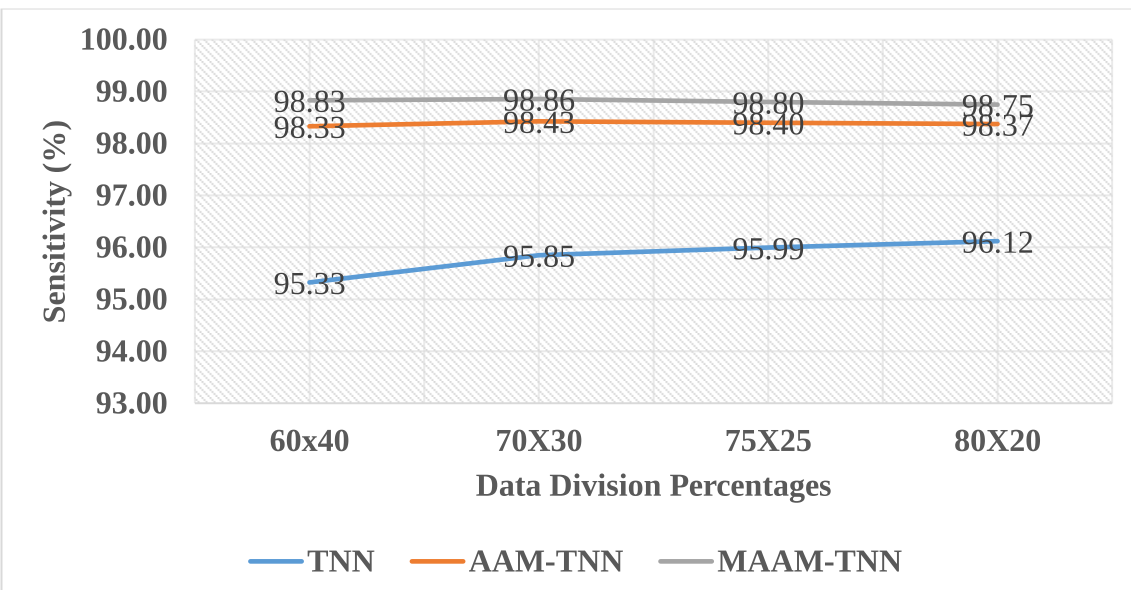

Figure 6: Graph of Sensitivity of Three Models shows MAAM-TNN achieving highest scores of sensitivity at 98.75 compared to 98.37 AAM-TNN and 96.12 TNN respectively.

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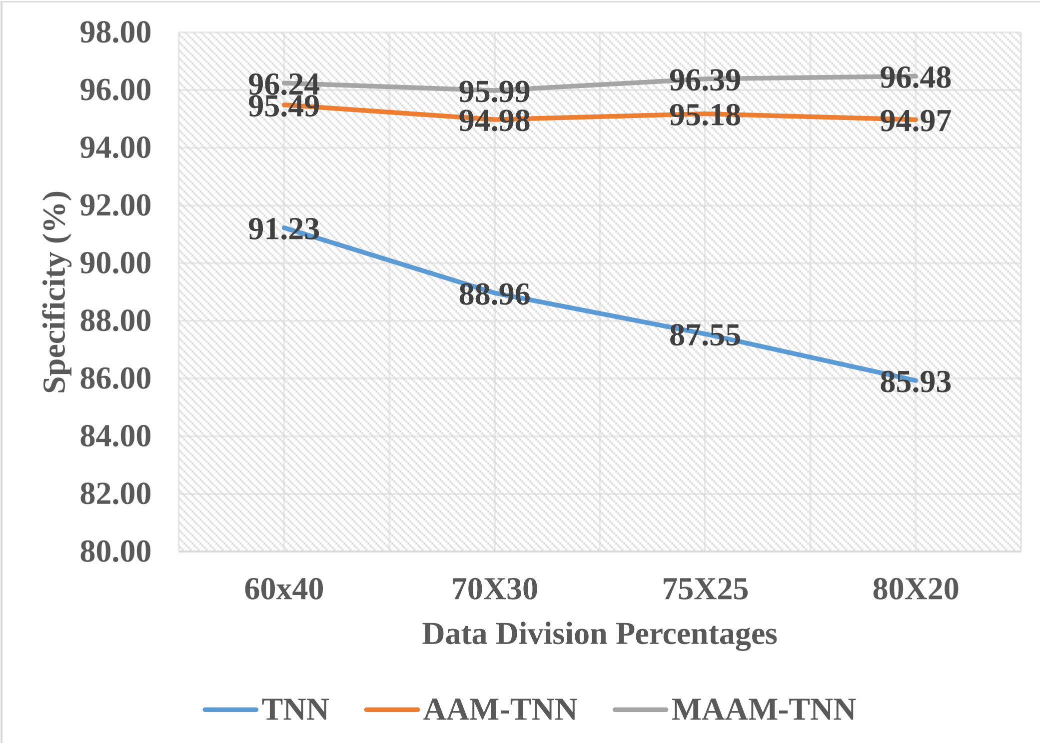

Figure 7: Graph of Specificity of Three Models: shows MAAM-TNN achieves the highest scores, reaching 96.48% compared to 95.49% for AAM-TNN and 91.23% for TNN.

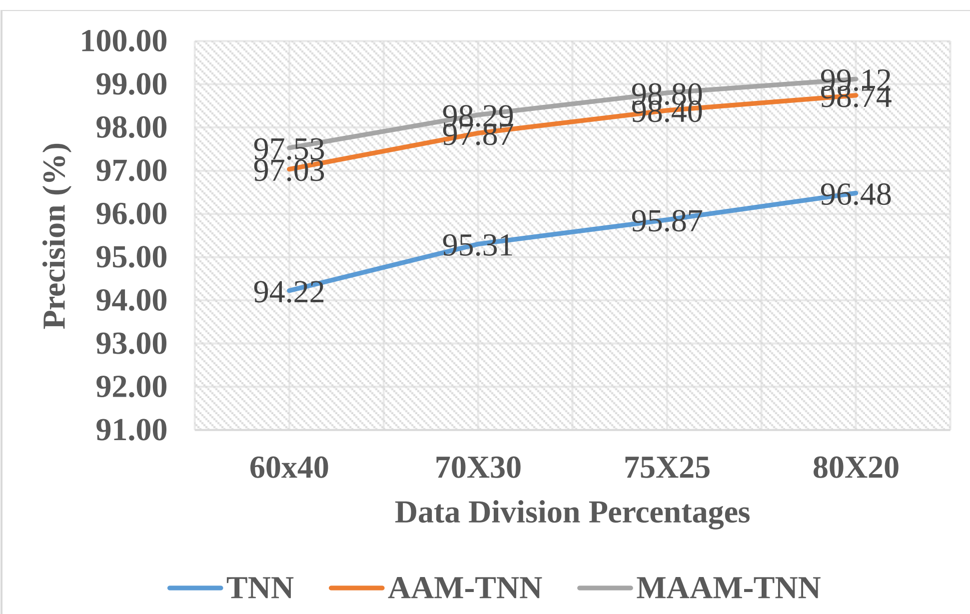

Figure 8: Graph of Precision of Three Models highlight MAAM-TNN's superiority, peaking at 99.12% versus 98.74% for AAM-TNN and 96.48% for TNN.

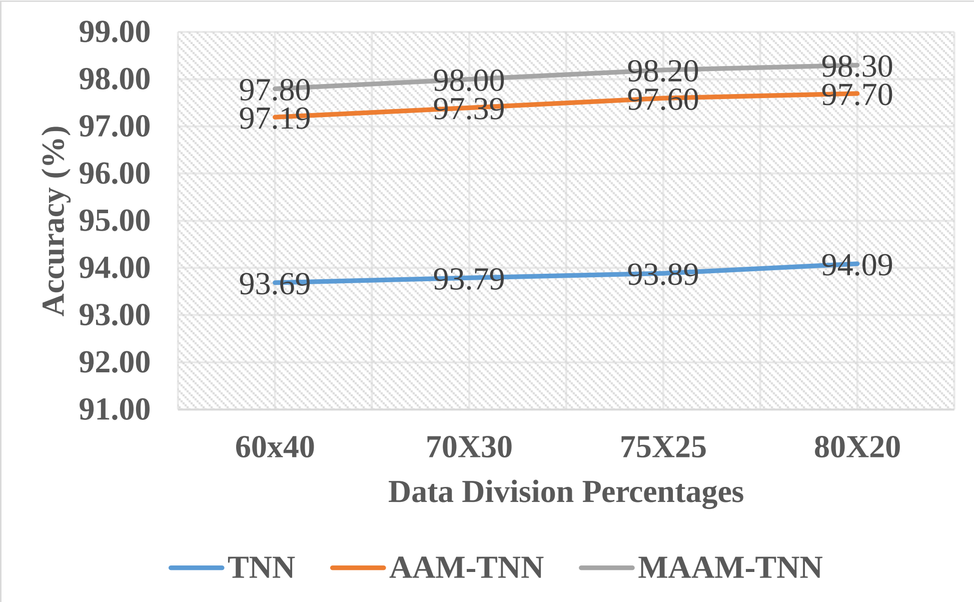

Figure 9: Graph of Accuracy of Three Models: show MAAM-TNN maintaining a strong lead with 98.30% performance at the 80:20 data split, while AAM-TNN reaches 97.70% and TNN trails at 94.09%.

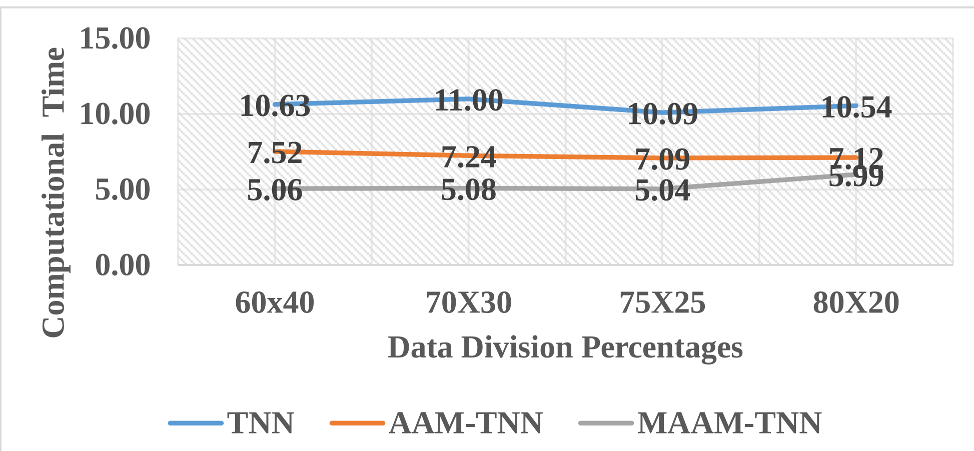

Figure 10: Graph of Computational Time of Three Models shows Computational time analysis reveals MAAM-TNN's superior computational performance, completing tasks in 5.99 seconds compared to 7.12 seconds for AAM-TNN and 10.54 seconds for TNN.

Conclusion

This study introduced the Modified Augmented Attention Mechanism for Tabular Neural Networks (MAAM-TNN) and demonstrated its superiority over both the baseline TNN and the intermediate AAM-TNN models for customer information profiling. The MAAM-TNN consistently achieved higher accuracy, sensitivity, specificity, and precision while maintaining a significantly lower false positive rate. This performance gains align with trends observed in recent attention-based tabular models, which similarly report improved discriminative power through adaptive feature weighting; however, MAAM-TNN extends this capability by capturing more nuanced contextual interactions within customer data. Beyond improved predictive quality, the model also delivered substantial computational efficiency,

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completing inference in under 6 seconds—faster than both AAM-TNN and standard TNN—making it highly suitable for real-time applications such as fraud detection, personalized marketing, and credit evaluation.

Despite these strengths, several challenges remain. The model's performance is influenced by the quality and representativeness of the training data, and like many deep learning systems, it requires considerable computational resources during training. Deployment in production environments must also account for data privacy, the secure handling of sensitive customer attributes, and compliance with regulatory requirements such as data protection laws. These considerations mirror limitations reported in comparable studies, underscoring the need for responsible AI deployment in financial and customer analytics domains. Future research should explore enhancements in model interpretability, the integration of federated learning to improve privacy preservation, and optimization for low-resource environments to increase deployment flexibility. Expanding validation across larger, multi-sector datasets would further strengthen generalizability and enable more robust comparison with emerging tabular-transformer and hybrid attention architectures.

MAAM-TNN emerges as a stable, deployment-ready solution for next-generation customer information systems. Its consistent performance across data splits (60:40 to 80:20), high predictive reliability, and low-latency inference demonstrate strong suitability for dynamic, real-world decision-making environments. By advancing attention-based modeling for tabular data, MAAM-TNN provides organizations with a powerful tool for enhancing customer personalization, improving risk assessment, and supporting strategic operational decisions.

Recommendations

i. It is strongly recommended that MAAM-TNN model should be deployed for real-time customer information profiling in critical business applications such as fraud detection and personalized marketing, given its demonstrated superiority with 98.30% accuracy, minimal 3.52% false positive rate, and rapid sub-6-second inference time—significantly outperforming both TNN and AAM-TNN.

ii. To further enhance predictive robustness against evolving customer behaviours, training data should be expanded to incorporate multi-source interactions including transactional histories, real-time behavioural streams, and cross-channel engagement patterns.

iii. For seamless operationalization, MAAM-TNN should be integrated into existing business infrastructures like CRM platforms, e-commerce recommendation engines, and mobile banking applications using API-first architectures to ensure compatibility with live data pipelines.

iv. Future research must explore hybrid architectures combining MAAM-TNN with gradient-boosting methods like XGBoost or transformer networks to address sparse feature challenges and highly imbalanced datasets. These hybrid frameworks should be rigorously benchmarked against standalone MAAM-TNN to quantify incremental gains in edge-case scenarios. Such enhancements will solidify the model's adaptability across diverse demographic segments while maintaining its real-time efficiency. Ultimately, these strategic steps will maximize the model's impact on dynamic customer profiling ecosystems.

Abbreviations

AI: Artificial Intelligence
AM: Attention Mechanism
AMM: Augmented Attention Mechanism
AT: Attentive Transformer
DO: Decision Output
DS: Decision Steps
GUI: Graphical User Interface
FM: Feature Masking
FPR: False Positive Rate
FP: False Positives
FN: False Negatives
FT: Feature Transformers
MAAM: Modified Augmented Attention Mechanism
ML: Machine Learning
ReLU: Rectified Linear Unit

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SGD: Stochastic Gradient Descent
TNN: Tabular Neural Network
TP: True Positives
TN: True Negatives

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