



AN IMPROVED MODEL FOR THE CLASSIFICATION OF CREDIT RISK USING HYBRID DEEP LEARNING APPROACH

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ABSTRACT

This study identified credit risk factors in the Nigerian banking sector and developed a hybrid deep learning model to improve credit facility engagements. Both secondary and primary datasets were employed. Secondary data were sourced from selected commercial banks and peer-reviewed publications, while primary data were gathered through Key Informant Interviews (KII) with experienced commercial bankers. Categorical features underwent data transformation, and feature importance was assessed using mutual information, which informed the generation of a reformed dataset. A Hybrid Deep Learning classification model was formulated and simulated using varying proportions of the hold-one-out method via Google Colaboratory. Model performance was evaluated based on accuracy, true positive rate, false positive rate, and precision. Six key features were identified as most relevant to credit risk classification: monthly income, annual income, amount invested monthly, outstanding debt, equated monthly installments, and type of loan. The DNN-based model trained on these features achieved a prediction accuracy of 99.9%, significantly reducing redundancy across the original 23 features and cutting processing time. Furthermore, the Hybrid model (combining an AutoEncoder with a Deep Neural Network) outperformed a standalone DNN-based model by 46.8%. The study concluded that selecting relevant features for predictive modelling tasks reduces model complexity, simulation time, and memory usage, collectively contributing to improved performance. These findings offer a practical framework for enhancing credit risk assessment in the Nigerian banking sector through intelligent, efficiency-driven machine learning approaches.

Keywords: Credit Risk, Deep Learning, DNN-based Model, Improved Model

INTRODUCTION

A loan that is given to a client or a financial instrument with pre-arranged regular installments that are collected during a specific amount of time is referred to as credit (Manab *et al.*, 2015). Credit risk is the possibility of losing valuable assets due to a counterparty's likely decline in creditworthiness or failure to fulfill contractual obligations (Anita, 2008). The primary operations of banks, which include lending money and accepting deposits, are linked to credit risk (Salihu and Shehu, 2020). Making decisions is a crucial part of choosing lenders with a great deal of expertise. The secret to high credit ratings is to recognize less risky consumers. Credit scoring refers to the formal statistical techniques used to categorize people seeking credit into "good" and "bad" classifications (Darwish and Abdelghany, 2016).

Credit scoring is used to divide applicants into two categories: those with excellent credit and those with poor credit. (Wang and Song, 2022). While the latter class has a higher likelihood of defaulting, the former class has a greater chance of meeting their financial responsibilities. Applications from people who fall into the "bad credit" category will be rejected. One of the biggest hazards that commercial banks face is credit risk, which is becoming more significant due to shifting regulations and erratic market conditions (Brkic *et al.*, 2017). Although credit risk is often assessed by commercial banks using different techniques and protocols, a loan officer's main responsibility is to assess an applicant's financial standing and determine whether or not the application can afford to pay back the bank loan that was requested.

Risk analysis techniques, both qualitative and quantitative, help experts control uncertainty in credit decision-making. While qualitative methods rely on judgment, quantitative approaches use statistical models. Risk-scoring models were originally designed to standardise credit decision-making, and

numerous such models have been developed to support credit admittance decisions. (Moscato *et al.*, 2021).

The 5Cs - Character, Capacity, Collateral, Capital, and Conditions - are the primary subjective metrics used by traditional financial institutions to assess borrowers' creditworthiness. (Kumar *et al.*, 2021). These metrics, especially for consumers living in rural areas, is mostly unable to evaluate borrowers who have limited banking activities and no loan history (Munkhdalai *et al.*, 2019). These conventional techniques, however, are unable to offer a thorough borrower profile. The financial services business is a domain having a variety of expert systems for its many applications, because the decisions in the finance sector are so complex and repetitious, in addition to standard scoring models (Mohammed and Salama, 2013). Algorithms for machine learning, deep learning, and artificial intelligence have all been taken into consideration and used in recent credit risk modeling methodologies (Wandmacher *et al.*, 2022).

Effective loan processing, model reliability, credit risk forecasting and monitoring are important parts of transparency and decision-making. Therefore, banks are using increasingly sophisticated techniques for evaluating credits by utilizing Machine Learning (ML) technology, which is particularly useful in forecasting a borrower's repayment patterns. (Tian *et al.*). Recent studies have revealed that learning architectures have shown better improvements at credit risk modeling compared to machine learning techniques (Chi *et al.*, 2019). This study made an attempt to explore this potential by developing a methodology for the development of a predictive model which can be adopted for classification of credit risks assessment using a combination of deep learning architectures.

Related Works

This section reviews prior work on credit risk modelling, covering both data-centric and rule-based approaches.

Shi *et al.*, (2022) conducted a systematic review of 76 scientific articles on machine learning applied to credit risk modeling (2014–2022). The findings revealed that deep learning outperformed traditional machine learning, while ensemble models outperformed single-algorithm models. However, the study did not explore hybrid deep learning architectures and was limited to single simulation runs.

Hasan *et al.*, (2021) explored the application of fuzzy logic to credit risk modeling for an organization. The variables considered in this study included information about the personal information of clients and their loan history alongside non-financial managerial factors. The study generated linguistic variables from 84 input variables for which 241 inference rules were extracted based on expert knowledge about the correlation between risk associated with credit and the variables. The model was validated using sample data from selected organization. The study's findings showed that the validation of the performance of the fuzzy logic model achieved an accuracy of 95.3%. Also, the confidence level of 5 experts about knowledge base fell between an interval of 80% to 92%. Assuming that each variable has 2 linguistic variables, the domain of inference rules should have at least 2^{84} rules which is clearly beyond the 241 rules extracted by the experts. The judgement of the experts regarding the information provided is clearly subjective as it lacked a large amount of knowledge about the evaluation of risk associated with credit.

Wang and Song (2022) developed a Takagi-Sugeno neuro-fuzzy model to assess credit risk among Chinese farmers using ten risk factors across four categories. The model effectively classified farmers into credit risk groups, though its risk factors were not transferable to the Nigerian credit risk context addressed in this study.

Hasan *et al.*, (2021) proposed a fuzzy logic model for credit risk assessment in Egypt, achieving 95.3% accuracy. The

model relied on expert-derived inference rules and was found to be subjective, limiting its objective representation of credit risk factors.

Kin *et al.*, (2021) developed the application of fuzzy logic to the development of a bankruptcy prediction model. The study identified a number of qualitative factors that are associated with the risk of bankruptcy namely industrial risk, management risk, financial flexibility, credibility, competitiveness and operational risk. The study adopted the use of 3 trapezoidal fuzzy membership function for representing the linguistic variables: negative, average and positive. Fuzzy inference rules were generated using the identified factors. The performance of the model was evaluated using real-life dataset. The study's findings showed that 25 inference rules were produced for the prediction model, and an examination of the model's performance indicated a 99.2% success rate. The study was focused on assessing bankruptcy from the perspective of a corporate body. The expected sample space of the inference rules with a value of 3^3 is 243 rules, which is larger than the 25 rules that was generated in the study.

Nyangena (2019) compared five machine learning algorithms for customer credit risk classification using 20,299 records, with gradient boosting achieving the best accuracy of 79.1%. The study confirmed the superiority of ensemble models but was limited to a single simulation run, raising concerns about the generalisability of the reported performance.

MATERIALS AND METHODS

Method

This study developed a hybrid AE-DNN architecture for credit risk classification, simulated over four train/test splits using Google Colaboratory. Performance was evaluated on accuracy, TP rate, FP rate, precision, and f1-score, and the best model was deployed as a web-based prototype in Python. Figure 1 illustrates the research framework, from feature identification through data collection, preprocessing, model development, and evaluation.

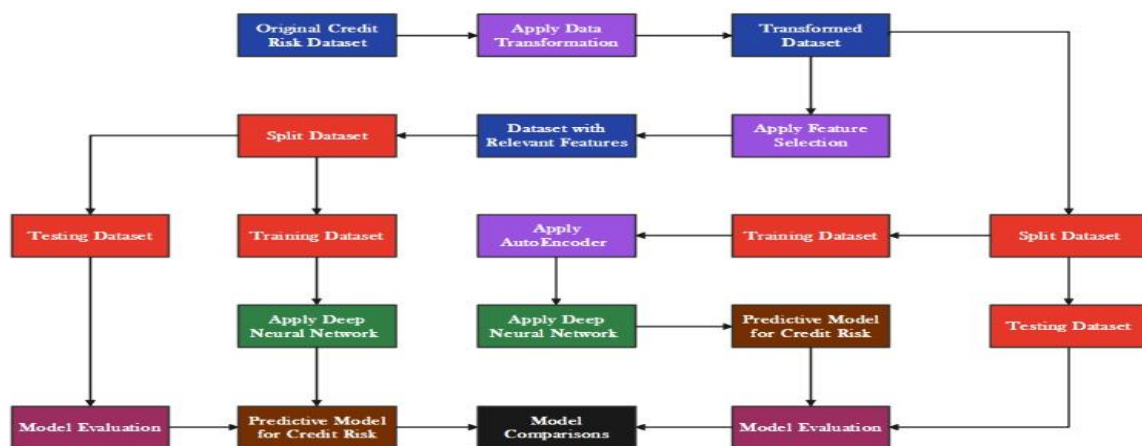


Figure 1: The Research Framework

Preprocessing involved removing client demographic identifiers and converting categorical string variables to integer-encoded numerical values, as required by deep learning algorithms.

The autoencoder (AE) layer re-engineered the input features to extract latent inter-feature relationships, enabling the DNN layer to develop a stronger understanding of the feature-target relationship.

Model development used the hold-one-out method with varying train/test proportions, evaluated on accuracy, true positive rate, precision, and f1-score.

Features for credit risk classification were identified from the literature and validated by experts with over ten years of experience in Nigerian commercial banking.

Table 1 describes the 23 features identified for credit risk classification, grouped into four categories: customer profile,

credit, payment, and account information, comprising seven categorical and 17 numerical variables.

Historical data were collected from credit institutions in south-western Nigeria, de-identified by removing all client demographic details, and stored in .csv format.

The preprocessed dataset was further analysed using mutual information, a filter-based, information-theoretic feature selection technique, to rank features by relevance to the target class and minimise redundancy.

The dataset was partitioned into four simulation runs with train/test splits of 60/40, 70/30, 80/20, and 90/10 using Google Colaboratory. Models were evaluated on accuracy, recall, precision, and f1-score, and the best-performing model was selected.

RESULTS AND DISCUSSION

Data were collected from Nigerian credit institutions and stored as a .csv file called credit_data.

The dataset contains 100,000 records across 23 features, classified as either poor (46,826) or standard (53,174) credit

risk. The class distribution (Figure 2) is not imbalanced, with only a 6.4% difference between classes.

The dataset was loaded into Google Colaboratory via Google Drive and imported as a DataFrame using pandas. Dataset inspection confirmed 100,000 records with 24 features, seven categorical (including the target class) and 17 numerical. Exploratory data analysis was conducted in two parts: categorical and numerical feature analysis.

Figure 3 shows the distribution of the classified credit risk records for the months when the loans were approved which revealed an equal monthly distribution of 12.5% each, with standard records consistently outnumbering poor records. Occupation analysis (Figure 5) showed lawyers (7.10%), engineers (6.87%), and architects (6.83%) as the most common clients. Credit mix analysis (Figure 6) revealed that most clients had standard credit mix (45.85%), while the majority of poor credit loans were associated with good credit mix (19.70%).

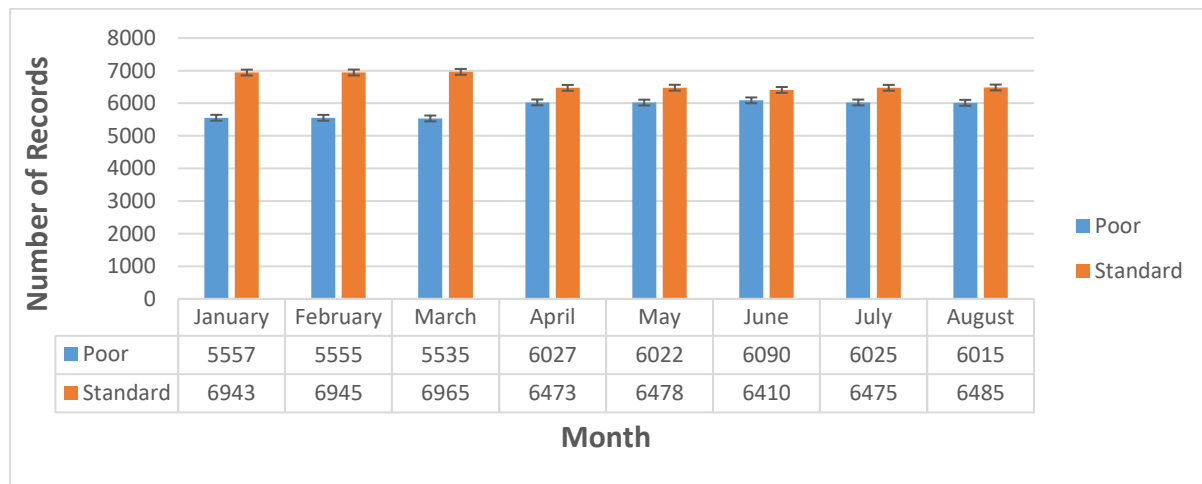


Figure 1: Bar Chart Distribution of the Number of Records across Months

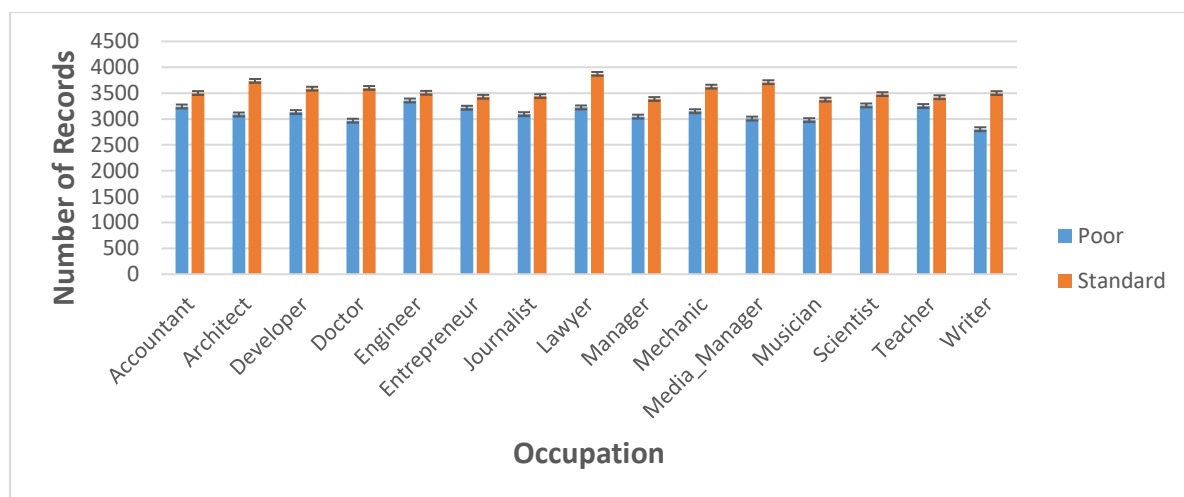


Figure 2: Bar Chart Distribution of the Number of Records across Occupation

Minimum payment analysis (Figure 7) showed 52.33% of clients had paid, while Figure 8 revealed most were low spenders with small payments (28.62%). Standard credit clients showed higher payment compliance and more frequent credit limit changes.

Equated monthly installments (Figure 12) were similarly distributed, though poor credit clients predominantly had installments below ₦250,000.

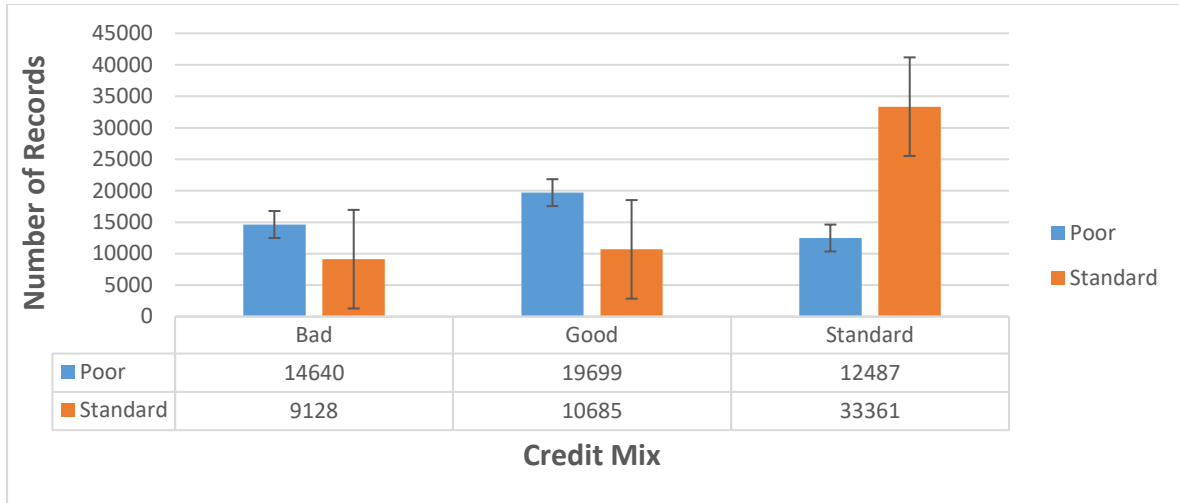


Figure 3: Bar Chart Distribution of the Number of Records across Credit Mix

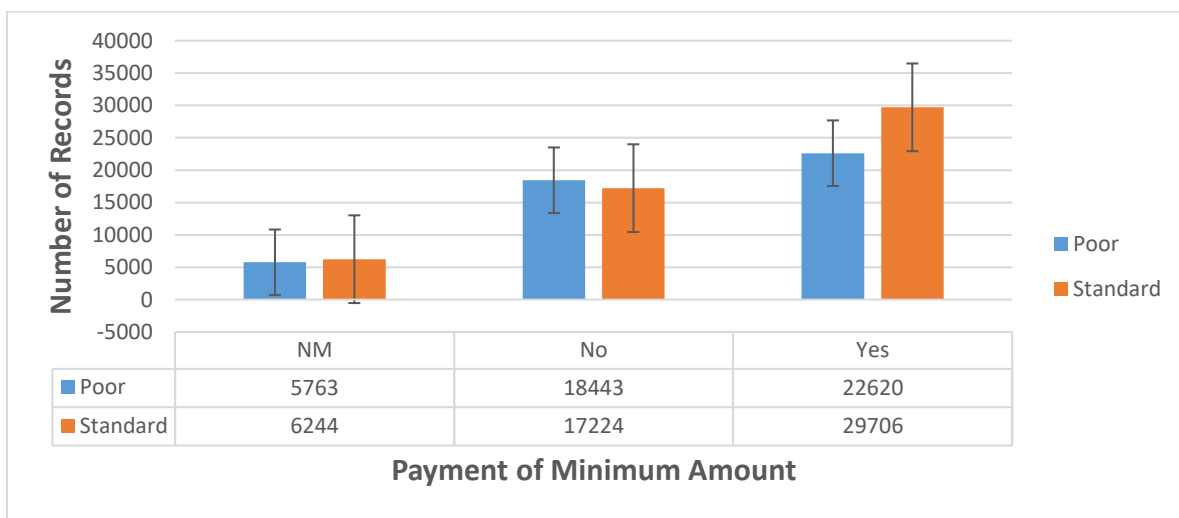


Figure 4: Bar Chart Distribution of the Number of Records Across Payment of Minimum Amount

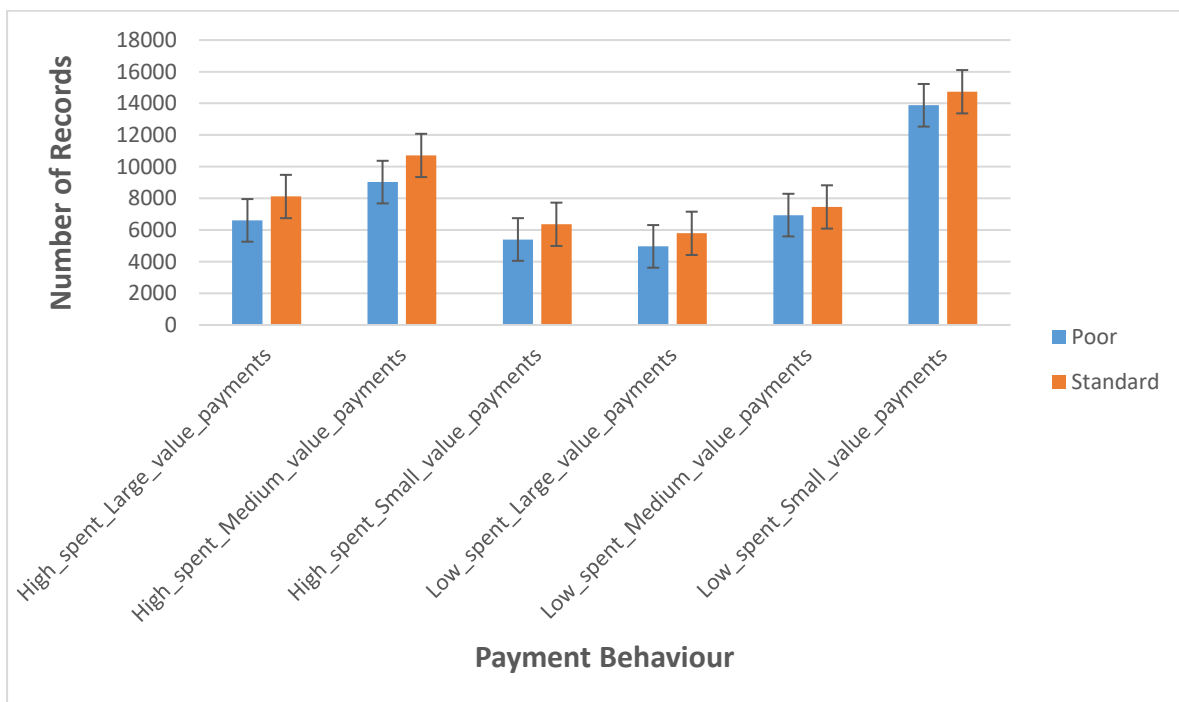


Figure 5: Bar Chart Distribution of the Number of Records across Payment Behaviour

Numerical features were analysed using bivariate box plots and histograms.

Figures 9 - 14 show the numerical feature distributions. Most credit loans were approved for clients aged 20 - 45 years, with younger clients more prevalent among poor credit records. Annual income (Figure 10) was similarly distributed across both classes, though clients with standard credit records had

higher maximum incomes, and the majority of poor credit records involved clients earning below ₦5 million annually. Figure 11 shows that standard credit clients experienced more frequent credit limit changes than poor credit clients, and the majority

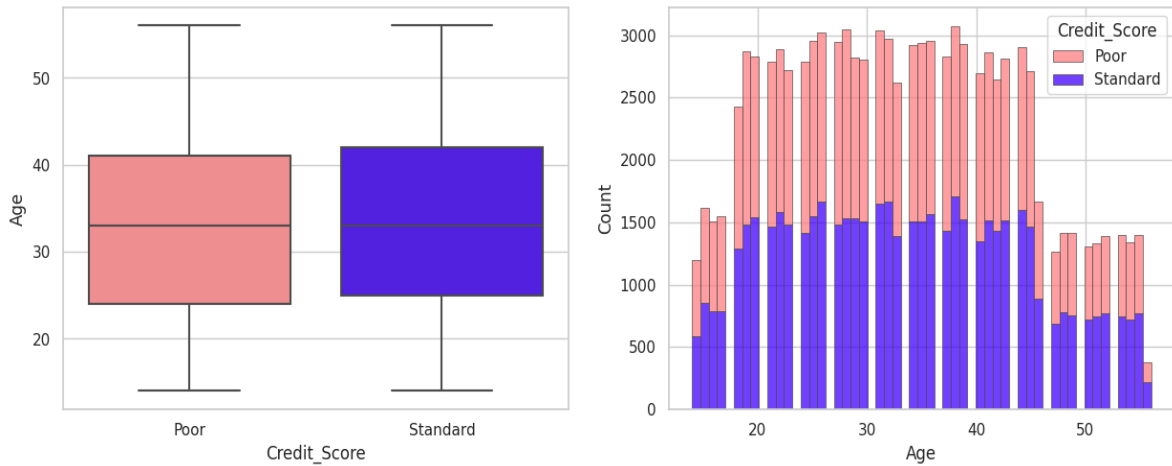


Figure 6: Distribution of the Age of Clients

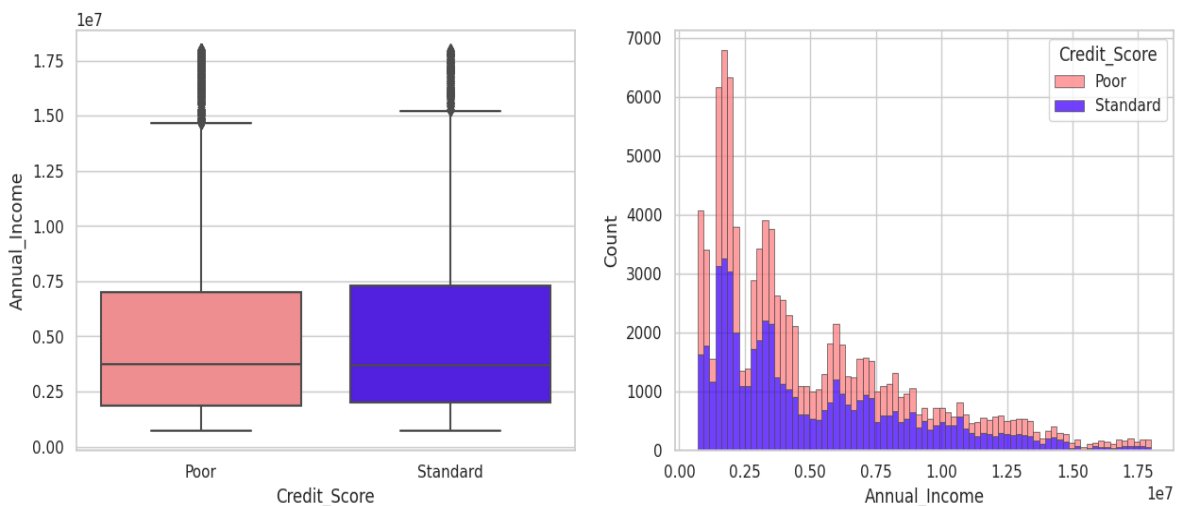


Figure 7: Distribution of the Annual Income of Clients

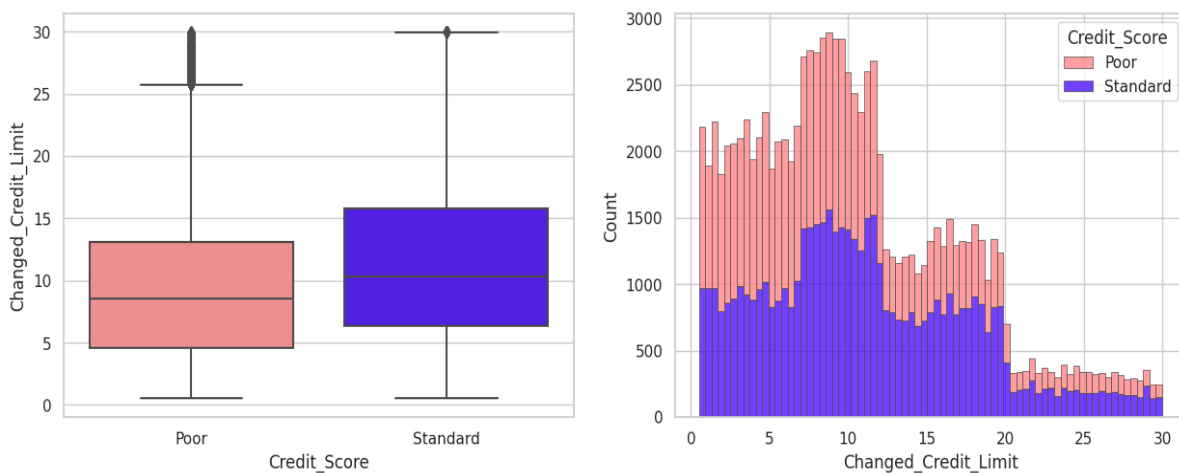


Figure 8: Distribution of the Number of Changed Credit Limit of Clients

Monthly investment amounts (Figure 13) were also broadly similar, with the majority of poor credit clients investing below ₦100,000 monthly.

Monthly balance distributions (Figure 14) showed that most poor credit clients maintained balances between ₦30,000 and ₦45,000.

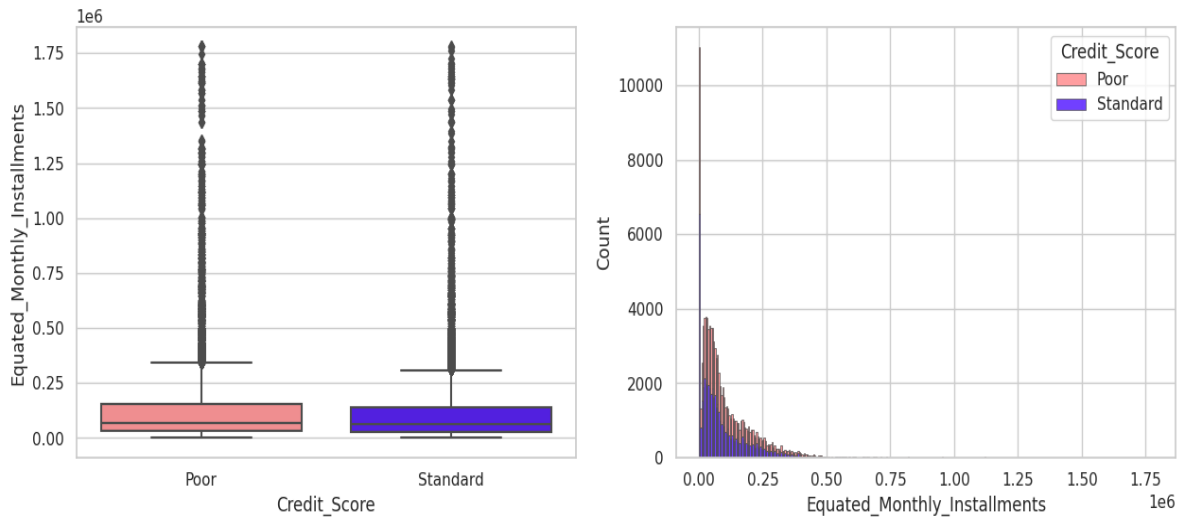


Figure 9: Distribution of the Equated Monthly Balance of Clients

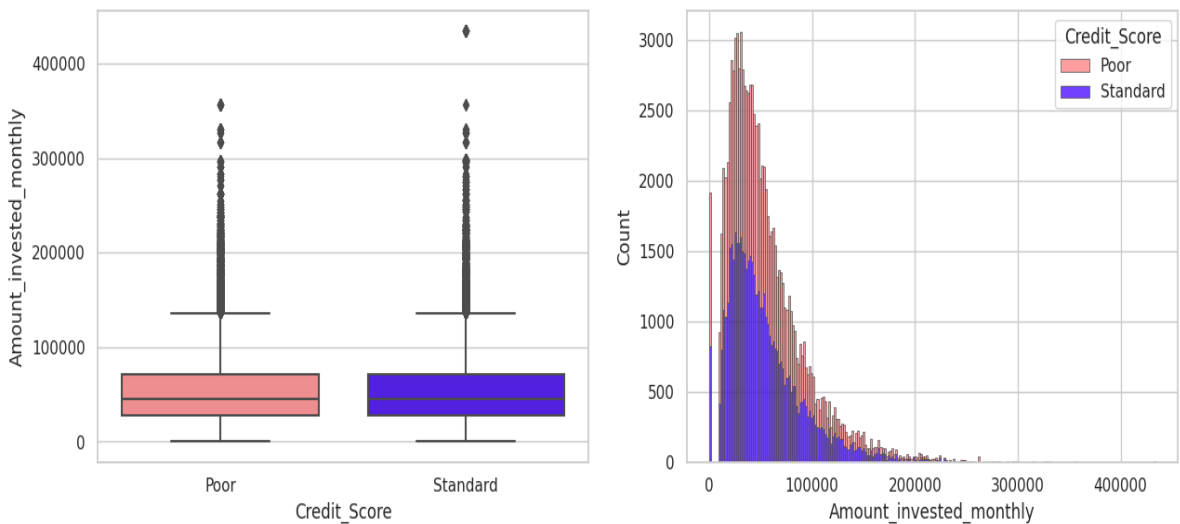


Figure 10: Distribution of the Amount Invested Monthly by the Clients

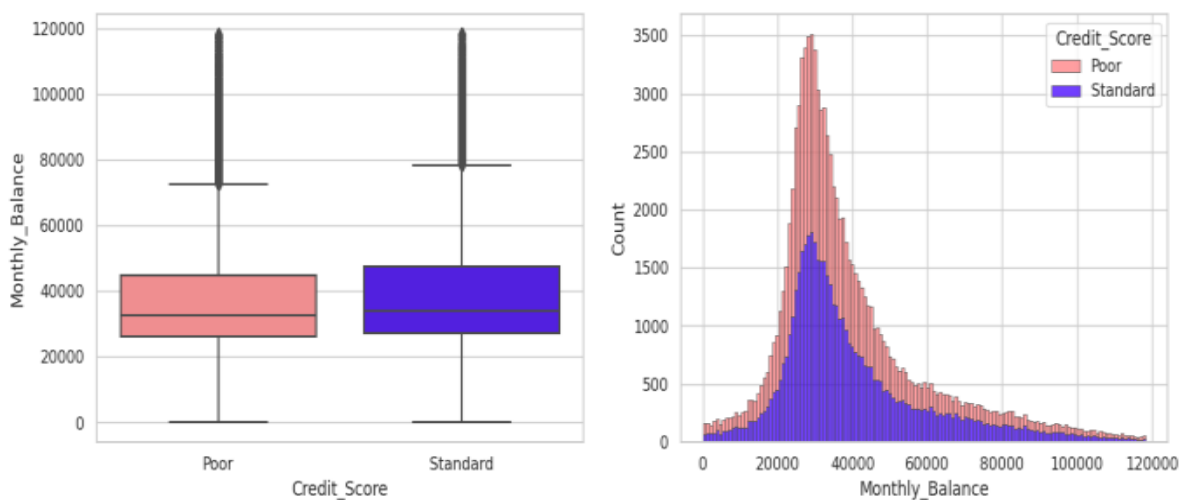


Figure 11: Distribution of the Monthly Balance of Clients

Categorical features were encoded as numerical values for Pearson correlation analysis, mutual information ranking, and deep learning simulation.

The process of feature importance was applied to identify which features most influenced credit risk classification, while Pearson's correlation assessed inter-feature relationships.

Mutual information was computed using The *sklearn.feature_selection* library was adopted for applying the mutual information as a basis of assessing relevance among the features. The mutual information of the features was estimated using the *mutual_info_classif* function. Figure 16 shows the source code and the results of the implementation of the mutual information function that was used to assess the relevance of the features and for ranking the features according to the value of mutual information.

The mutual information scores identified monthly income (0.342), annual income (0.339), and amount invested monthly (0.338) as the top three features, followed by outstanding debts (0.328), equated monthly installments (0.309), type of

loan (0.168), credit mix (0.071), and interest rate (0.043). These results confirm that income-related and debt-related features are the most critical determinants of credit risk, while payment behaviour features showed negligible relevance.

The scatter plot of the 23-feature dataset (Figure 17) revealed a large area of overlap between poor and standard credit records, highlighting the need for feature selection to improve class separability.

Three additional feature subsets were generated, top 18 (*relevant_features1*), top 12 (*relevant_features2*), and top 6 (*relevant_features3*), and scatter plots assessed class separability across each. Scatter plots were used to assess the distribution of the credit risk class records among the generated datasets.

Figure 18 shows scatter plots for the top 18, 12, and 6 ranked feature subsets. The area of class overlap progressively decreased with fewer features, confirming that selecting the most relevant features substantially improves credit risk class separability.

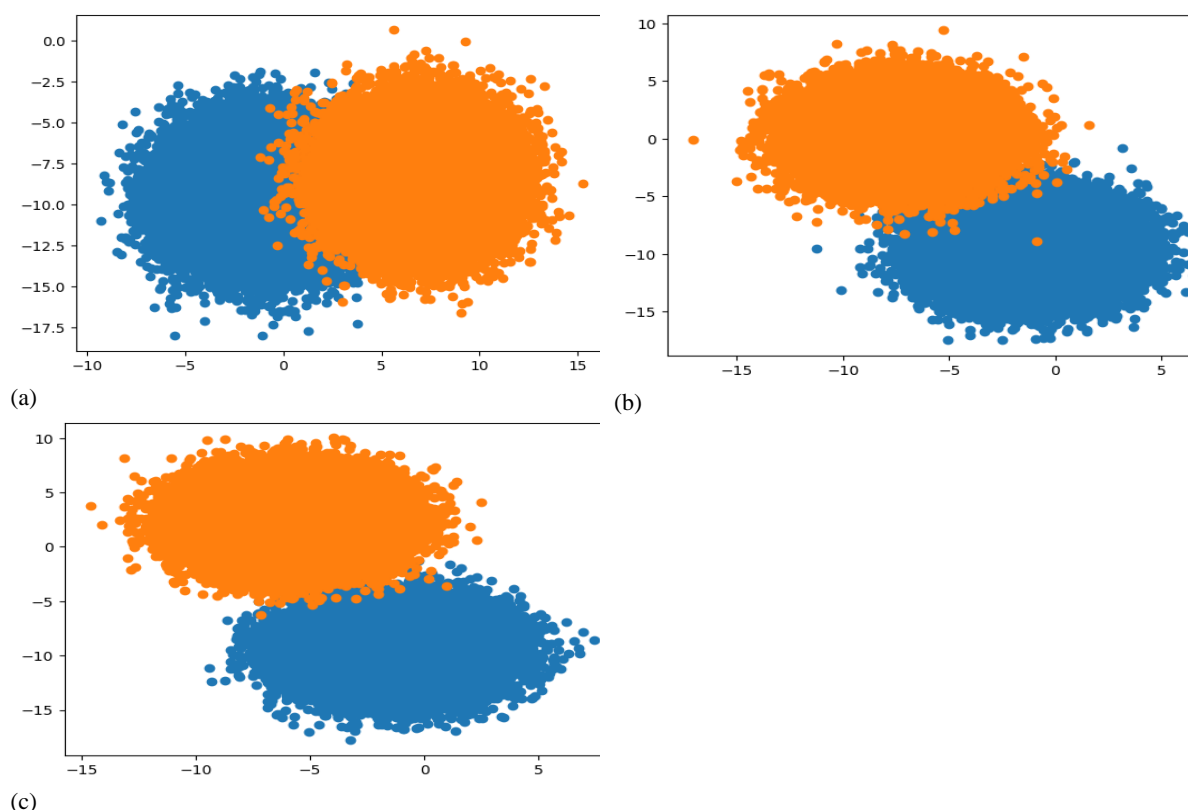


Figure 13: Scatter Plot of the Distribution of Credit RISK class Records among Dataset Containing Information about Top 18 Ranked Features (a), Top 12 Ranked Features (b) and Top 6 Ranked Features (c)

The *sklearn.model_selection* library was adopted for applying the Pearson's correlation as a basis of assessing the cause-and-effect relationship that may exist among the features. The feature-feature correlation of the features was estimated using the *cor* function. Figure 19 indicates the results of the feature-feature correlation using a heat map such that the red colours imply a positive relationship while blue colours imply a negative relationship and the deeper colours were used as a

basis for interpreting stronger positive or negative relationships between features.

The correlation heatmap (Figure 19) revealed strong positive relationships between annual and monthly income (1.0), amount invested monthly and income (0.81), and credit mix with interest rate (0.75) and delayed payments (0.76). Most credit behaviour features showed moderate positive inter-correlations, with a moderate negative relationship to credit history age.

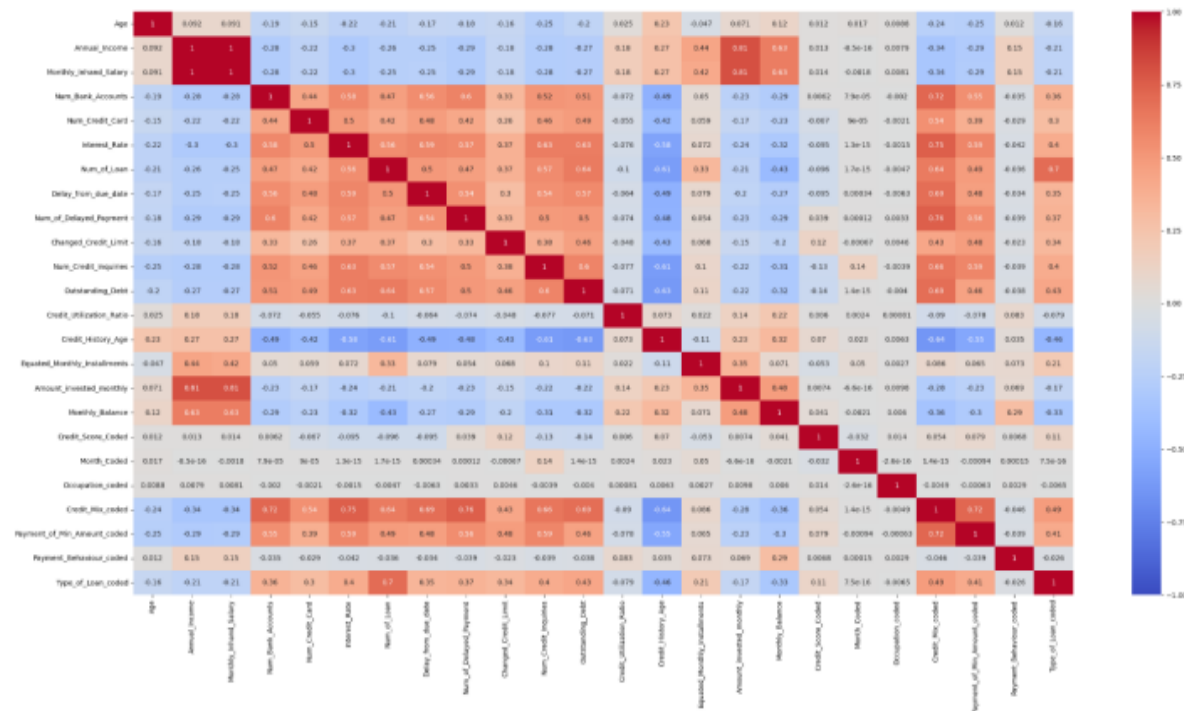


Figure 14: Results of the Heat Map Generated for the Feature-Feature Correlation

Table 1 summarizes the train/test split proportions used across the four simulations. Four simulation runs were conducted using train/test splits of 60/40, 70/30, 80/20, and 90/10.

Table 1: The Number of Records Stored in the Training and Testing Records

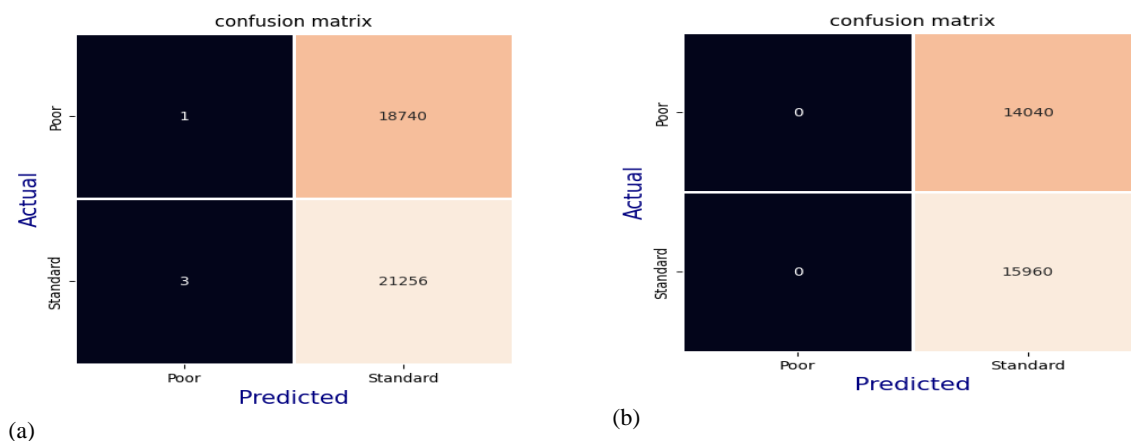
Simulation#	Train/Test Proportion (%)	Train Records	Test Records
Simulation1	60/40	60000	40000
Simulation2	70/30	70000	30000
Simulation3	80/20	80000	20000
Simulation4	90/10	90000	10000

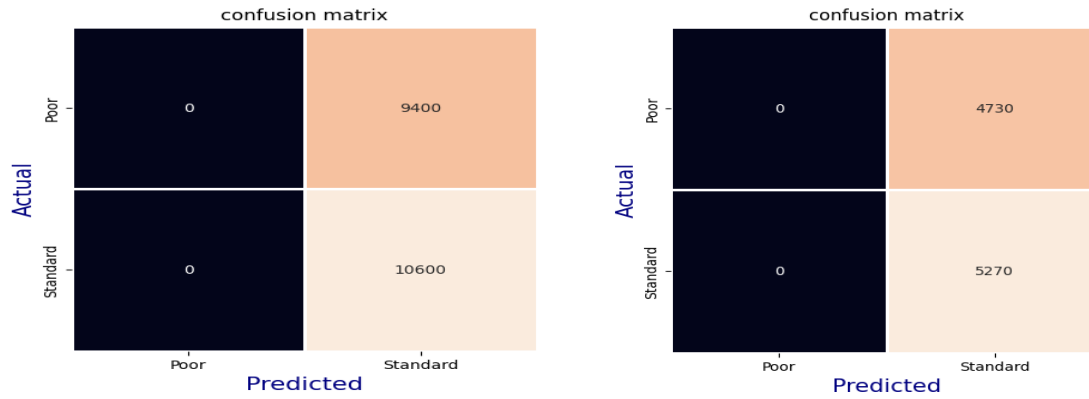
The Simulations were run using the DNN architecture across four feature subsets (23, 18, 12, and 6 features), followed by the hybrid AE-DNN architecture trained on all 23 features. Results are presented in the sub-sections below.

Figure 20 presents confusion matrices for the DNN model trained on all 23 features.

As shown in Figure 20 (a–d), the DNN model trained on all 23 features achieved limited discrimination between credit

risk classes across all four simulations, with accuracy ranging from 53.00% to 53.20%. In each simulation, the model correctly classified nearly all standard credit records but failed to identify the majority of poor credit records, indicating that the full 23-feature set introduced redundancy that impaired classification performance.

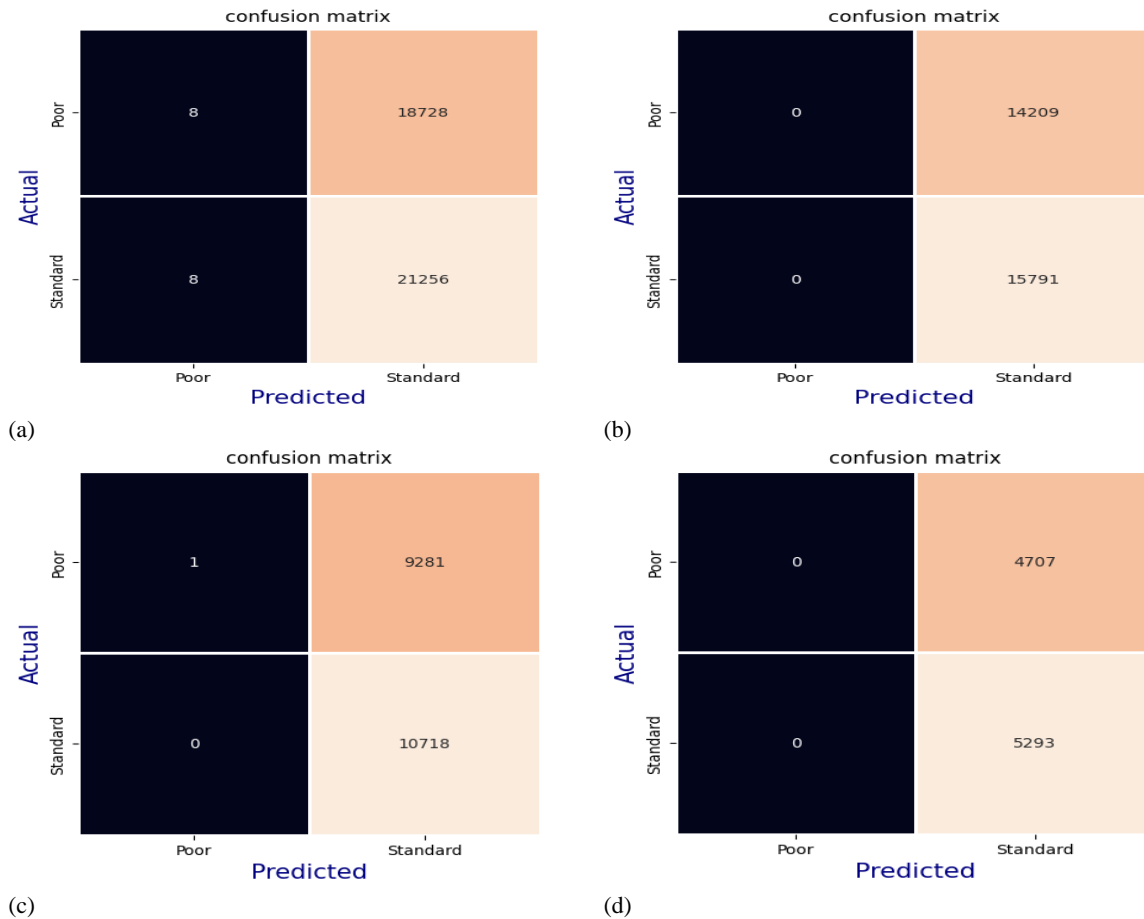




(C) (d)
Figure 15: Confusion Matrices for the Simulation of the Predictive Model using the Deep Neural Network (DNN) Architecture based on Information about 23 Features

Figure 21 shows confusion matrices for the DNN model trained on the top 18 features. As shown in Figure 21 (a–d), the DNN model trained on the top 18 features produced similarly limited results, with accuracy ranging from 52.64% to 53.60% across all four

simulations. The model largely failed to classify poor credit records correctly, suggesting that reducing from 23 to 18 features provided insufficient improvement in class separability.



(a) (b) (c) (d)
Figure 12: Confusion Matrices for the Simulation of the Predictive Model using the Deep Neural Network (DNN) Architecture Based on Information about Top 18 Features

Figure 22 shows confusion matrices for the DNN model trained on the top 12 features. As shown in Figure 22 (a–d), the DNN model trained on the top 12 features demonstrated partial improvement, achieving accuracy between 49.69% and 52.64% across the four

simulations. Unlike models trained on 23 or 18 features, this model was able to classify some poor credit records correctly, though its overall performance remained below that achieved with fewer features.

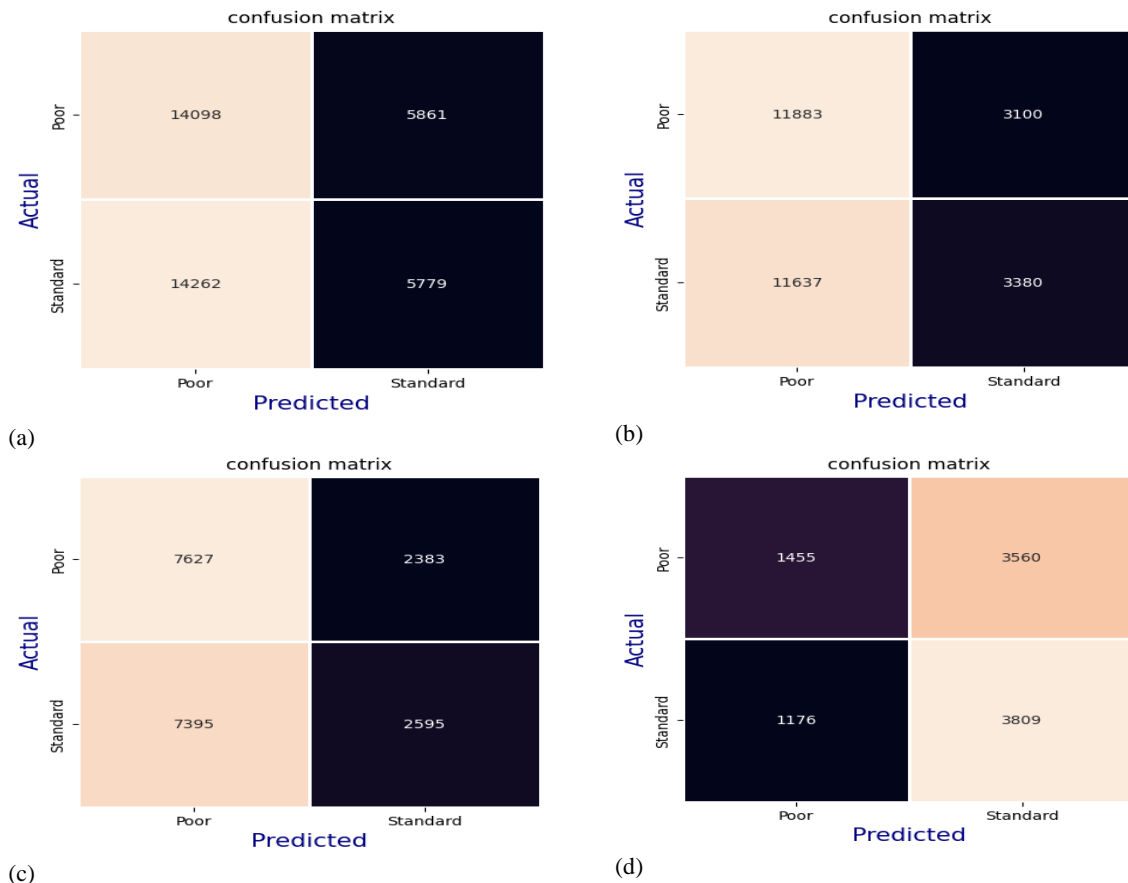
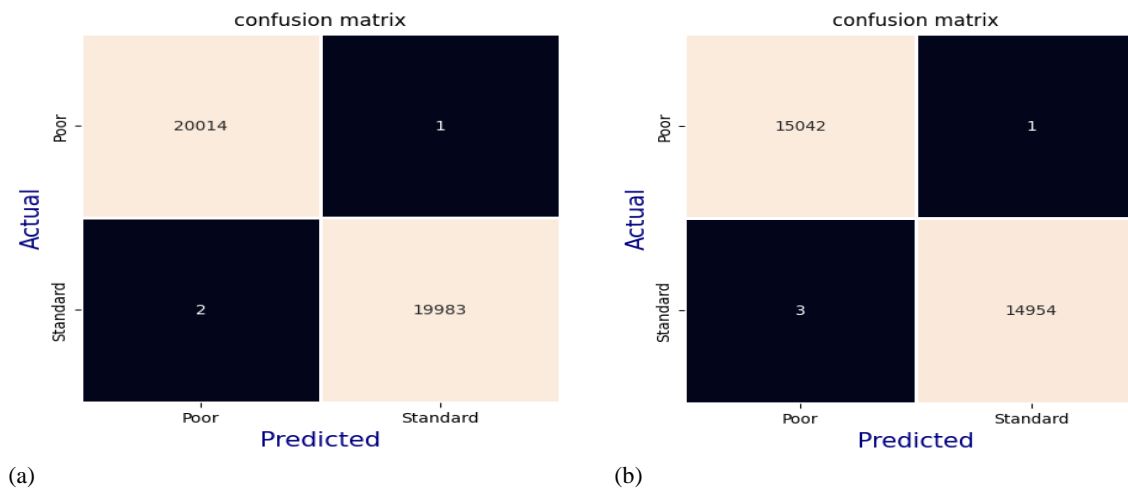


Figure 13: Confusion Matrices for the Simulation of the Predictive Model using the Deep Neural Network (DNN) Architecture based on Information about Top 12 Features

Figure 23 shows confusion matrices for the DNN model trained on the top 6 features.

As shown in Figure 23 (a - d), the DNN model trained on the top 6 features achieved a dramatic improvement in classification accuracy, ranging from 99.97% to 100.00%

across all four simulations. The model correctly classified virtually all poor and standard credit records in every simulation, demonstrating that the six most relevant features contained sufficient discriminative information for near-perfect credit risk classification.



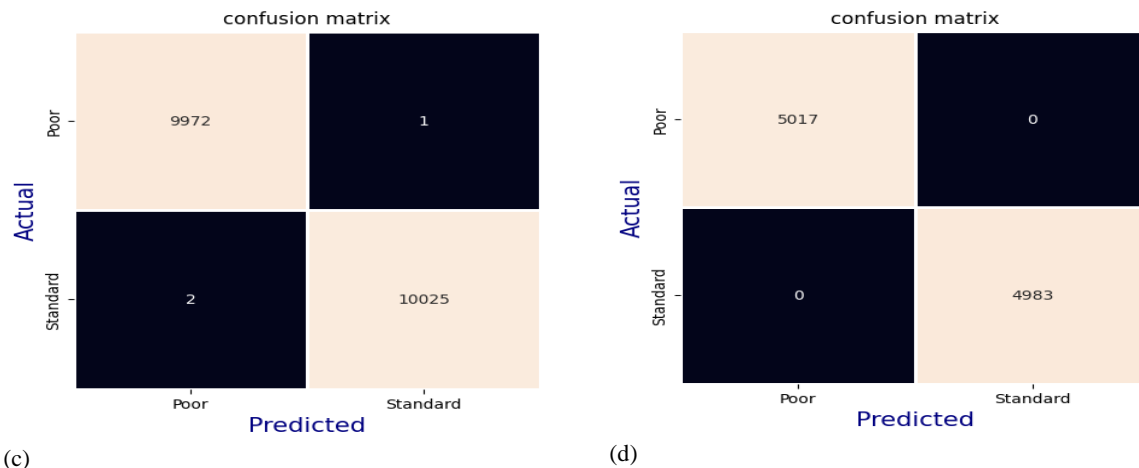


Figure 14: Confusion Matrices for the Simulation of the Predictive Model using the Deep Neural Network (DNN) Architecture based on Information about Top 6 Features

Figure 24 shows confusion matrices for the hybrid AE-DNN model trained on all 23 features. As shown in Figure 24 (a - d), the hybrid AE-DNN model trained on all 23 features achieved perfect classification accuracy of 100.00% across all four simulations. In every

simulation run, all poor and standard credit records were correctly classified without exception, confirming the superiority of the hybrid architecture in extracting discriminative feature representations even from a high-dimensional, redundant feature space.

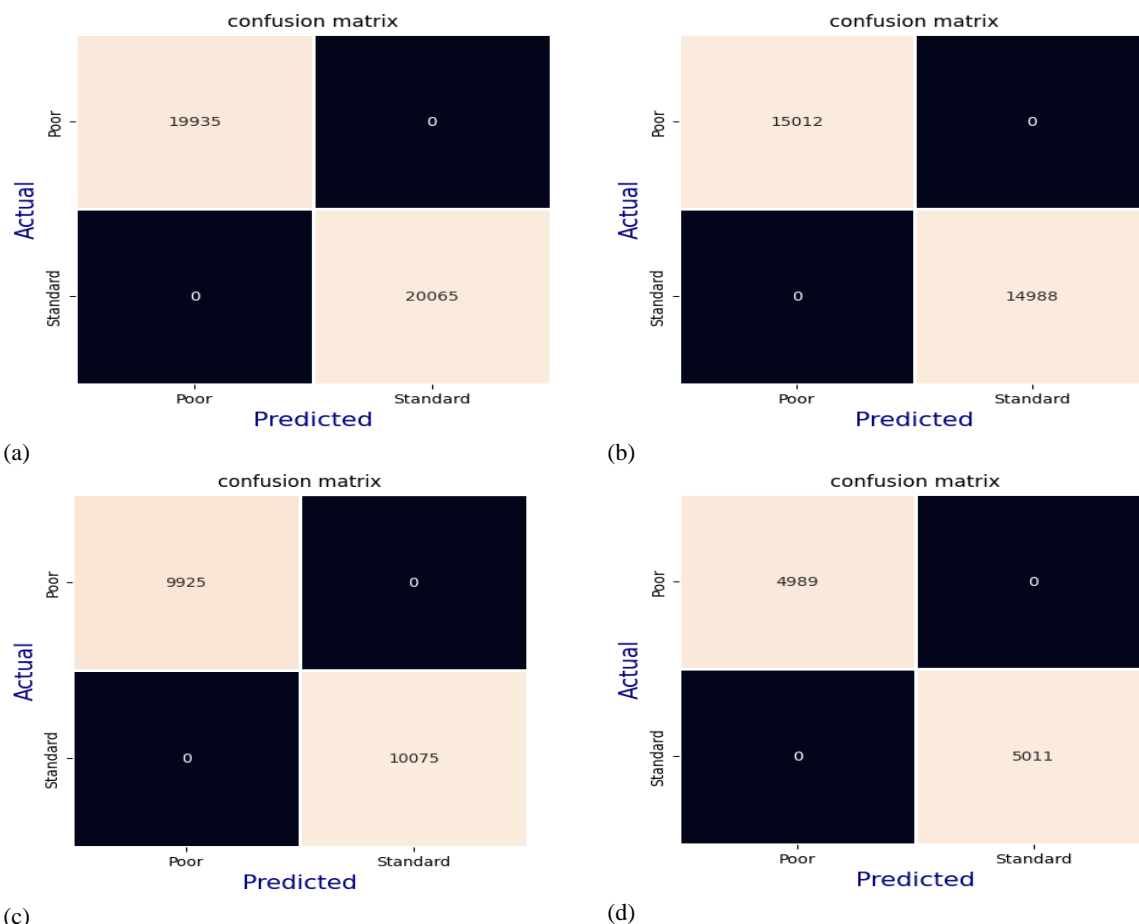


Figure 15: Confusion Matrices for the Simulation of the Predictive Model using the Hybrid Auto-encoder Deep Neural Network (AE-DNN) Architecture based on Information about 23 Features

The model performance improved as the training proportion increased from 60% to 90%, reflecting the benefit of more training data. The DNN model trained on 23 features only

outperformed the 12-feature model, except in simulation 3 (80% training) where it also surpassed the 18-feature model. Figure 25 shows that the DNN model with top 6 features achieved the highest accuracy among DNN variants, while the

AE-DNN model trained on all 23 features achieved the overall best performance. Figures 26 and 27 compare accuracy differences and recall/precision/f1-score across architectures. DNN models trained on 23 or 18 features failed to classify poor credit records, correctly identifying only standard credit cases.

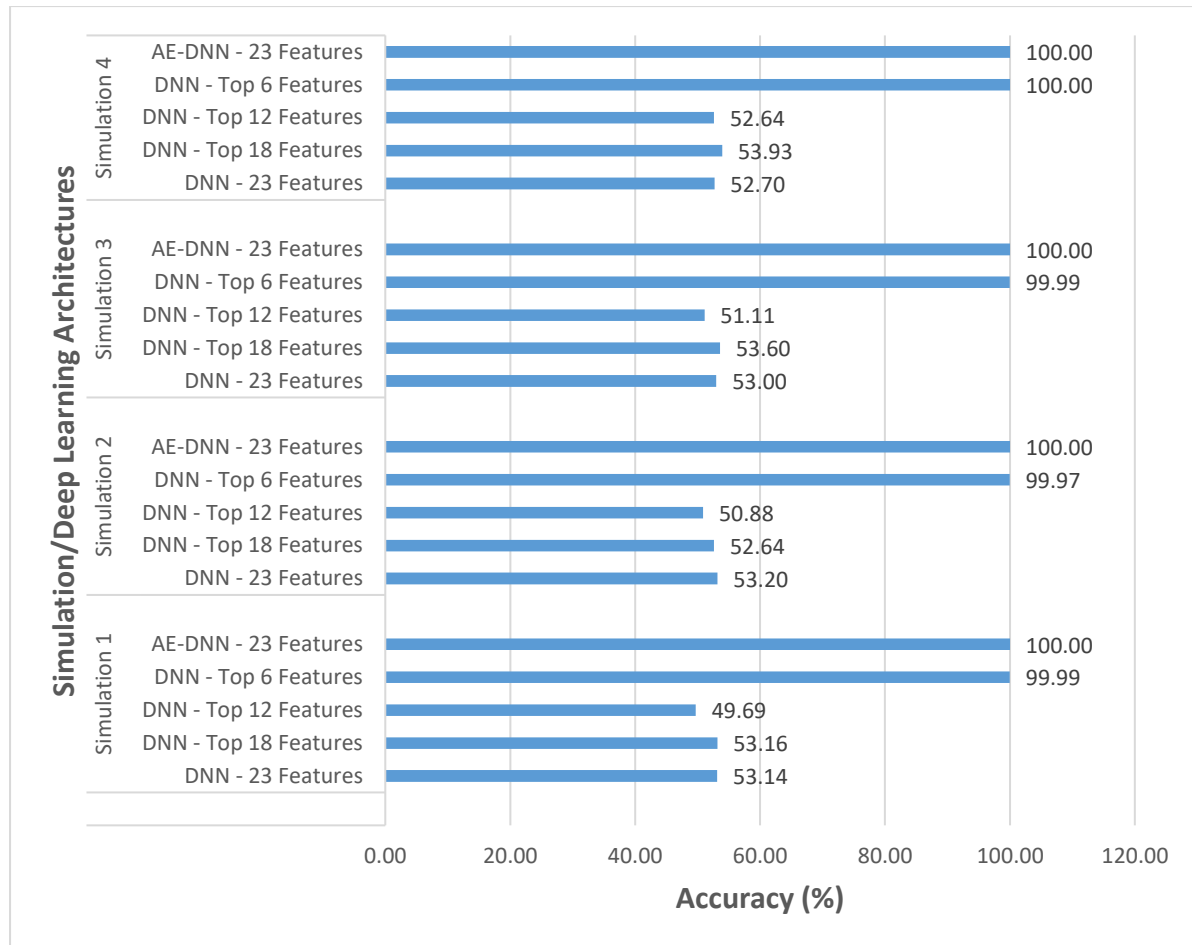


Figure 16: Bar Chart Plot of the Accuracy of Predicted Values Generated across four Simulations for the deep Learning Architectures

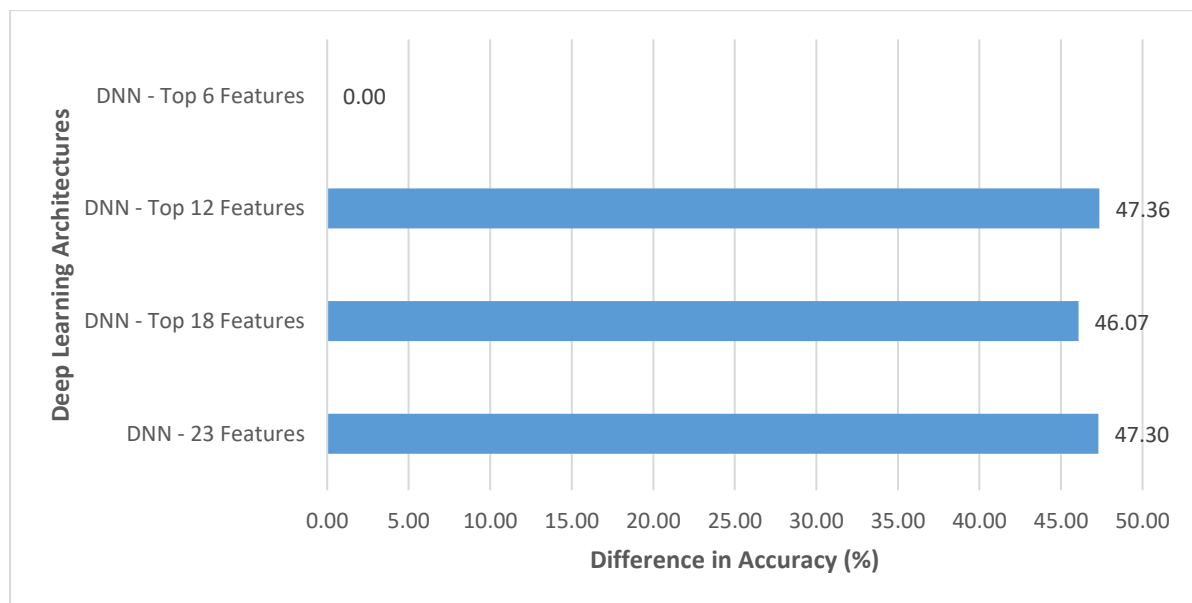


Figure 17: Bar Chart Plot of the Relative Difference between the Accuracy of the Performance of the Hybrid AE-DNN Architecture and the DNN Architecture

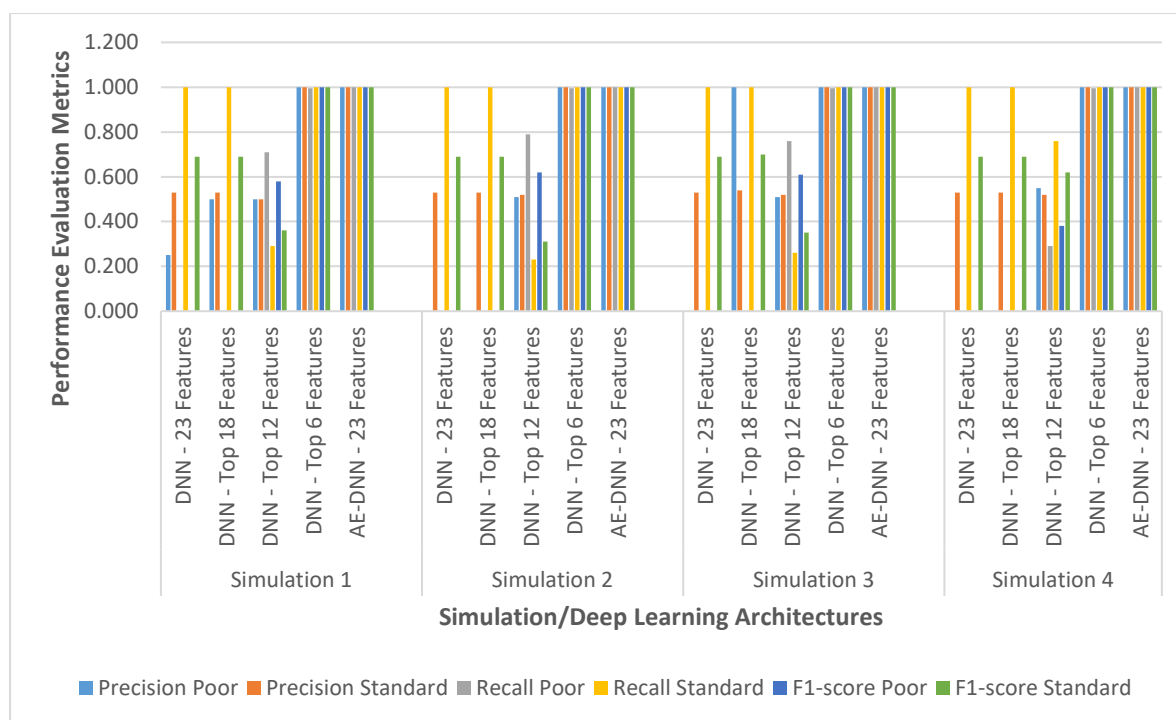


Figure 18: Bar Chart Plot of the Recall Precision and F1-score of the Target Classes (Poor and standard) for the Deep Learning Architectures Simulated over Four Simulations

While the 12-feature DNN model partially distinguished between classes, the 6-feature DNN and the AE-DNN model trained on all 23 features both effectively separated poor and standard credit records, confirming their suitability for credit risk classification.

CONCLUSION

The study concluded that the features associated with the classification of credit risk have a relative level of importance with respect to each other as some features are deemed to have more impact than others in the classification of credit risk.

It was concluded that the six most important features among the features that are associated with the classification of credit risk include monthly income, annual income, amount invested monthly, outstanding debt, equated monthly installments and type of loan. As such, the income is the most important feature to be considered among the customer's profile, the type of loan and the outstanding debt are the most important credit-based information to be considered, the equated monthly installments (EMI) and amount invested monthly are the most important account information to be considered. However, none of the payment information seemed to have any relevance or importance in the classification of credit risk. It was concluded that adopting a hybrid of deep learning algorithms provided better performance even in the presence of features that had little or no importance in the classification of credit risk.

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