

## DEVELOPMENT OF DEEP BELIEF NETWORK MODEL FOR CREDIT CARD FRAUD DETECTION

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### Abstract

Credit card fraud detection (CCFD) has attracted various critical research interest owing to increase in fraudulent activities in financial transactions. Machine learning and rule-based system, often struggle to solve the inherent challenges of imbalanced transactional datasets, concept Drift, real-time detection and Feature Engineering. Hence, this study developed credit card fraud detection system by employing a light weight deep belief network (DBN) model. The DBN which can learn hidden pattern of imbalanced dataset was formulated with 2 hidden layer, 244 neurons and 0.00921 learning rate. The architecture was formed using stacked layers of restricted boltzman machine while weight and biases were updated using contrastive divergence technique. The model performance on CCFD was accompanied on 10,000 transactional records with imbalanced ratio of 98:2 legitimate to fraudulent datasets. The result shows an average of 96.48% sensitivity, 96.36% precision, 95.66% F1-score and 94.96 accuracy for DBN-CCFD as compared to 95% sensitivity, 88% precision, 91% F1-score and 94% accuracy of DBNex. This study realized that a light weight architectural through careful selection of BDNs hyperparameters can result in excellent performance, providing a new direction for fraud detection system design that prioritizes efficiency without sacrificing accuracy.

### Keywords

*Credit card, Imbalance dataset, Machine learning, Deep belief network, Contrastive divergence*

## 1. INTRODUCTION

Credit card fraud denotes an illicit or unauthorized use of an account by individuals other than the legitimate owner, necessitating preventive strategies to curb such misuse. Specifically, it occurs in a process where someone exploits someone else credit card details for fraudulent personal benefits or personal gain without the authorization of the legitimate owner of the financial account [1].

The financial fraud techniques have become a foremost problem in the financial institutions because fraudsters are coming up with increasingly sophisticated transactions. [2]. Due to increase in e-commerce, digital banking or internet banking, cybercriminals have found new ways to exploit openness in payment systems [3]. Financial credit card fraudulent act has been found to be a world-wide challenge and losses are estimated to exceed \$40 billion a year by 2027. The conventional fraud detection methods do not possess the flexible ability to adjust to the changing fraud techniques [4]. Thus financial institutions are increasingly turning to artificial intelligence and machine learning to develop fraud recognition systems [5]. These technologies help in identifying suspicious patterns and mitigate problem of false positives that do occur in fraud detection.

Machine learning fraud detection models use historical transaction data to differentiate between legitimate and fraudulent activity [6]. Supervised learning models like random forests, neural networks and decision trees have also shown significant predictive power to detect deceptive transactions. [7]. In addition, anomaly detection and clustering which are unsupervised learning strategies were been used to identify previously undocumented fraud patterns [8]. However, fraudsters continuously adapt their tactics, making it necessary for fraud detection models to be regularly updated [9].

One of the better or stronger alternatives available in fraud recognition is deep learning models, because it possesses the ability to extract complex features automatically from large transaction datasets. [7]. Deep learning models, which are Recurrent Neural Networks (RNNs), Deep Belief Networks (DBNs) and

Convolutional Neural Networks CNNs does exhibit superior performance in detecting fraud transactions [10]. The deep learning models has the capability to process multi-step transactional data and identify patterns of fraud that are to a large extent not been fully exploited by traditional methods.

Within deep learning models available, DBNs have showed promising results in the way it processes fraud detection in credit card as a result of their hierarchical learning structure [11]. Deep belief networks consist of numerous layers of Restricted Boltzmann Machines (RBMs) which learn abstract representations of transaction data [12]. The DBNs captures complex correlations between different transaction attributes with hierarchical deep architecture, which enables them to be effective in fraud detection tasks [13]. DBNs can learn feature representations without extensive manual feature engineering, unlike shallow machine learning models [14]. Hence, they provide higher accuracy and generalization in detecting fraudulent transactions. As fraud techniques become more sophisticated, leveraging DBNs and other deep learning models will be crucial in minimizing financial losses and ensuring secure transactions on financial data and customer money.

[15] applied Deep Belief Networks(DBNs) to credit card fraud detection. Using a dataset containing more than 2-million credit card transaction records from a major U.S. financial institution, they evaluated a deep belief network based on restricted Boltzmann machines, which first performs unsupervised pre-training on training data and then fine-tunes the parameters using backpropagation. Experimental results show that their DBN method provides better accuracy (93.5%) and the false positive rate is 2.8% compared with other widely-used methods such as logistic regression and decision trees. The drawback of their method is high cost during the training step of the model, and it's difficult for financial institutions that have limited computational power to use real-time model updates.

In another approach, [16] implemented a neural network-based fraud detection system. The presented work focused on feature selection and threshold optimization for fraudulent detection using a Neuroph IDE. The results demonstrated the potential use of neural networks in increasing detection rates. The limitations and research gap in this work are that the work lacks the comparative analysis of emerging deep learning architectures and has computational inefficiencies in processing large-scale data, which diminishes the work's relevance to contemporary systems.

Computational efficiency of deep learning models for large-scale fraud detection was examined by [17]. Deep belief networks (DBNs), convolutional neural networks (CNNs), and long short-term memory networks (LSTMs) were tested on a dataset of 10 million transactions. Training time, inference speed, and resource consumption were measured. DBNs were the most efficient models, although they were slightly less accurate than CNNs and LSTMs. The trade-off between efficiency and efficacy remains to be resolved.

Detection of fraud in credit cards using the latest machine learning and deep learning methods was studied by [18]. Extreme Learning Methods, Decision Tree, Random Forest, Support Vector Machine, Logistic Regression XG Boost, and CNN were among the machine and deep learning models used in the study. The CNN had the highest accuracy (99.9%), precision (93%), and F1-score (85.71%). The research gap of this work includes problems with class imbalance or overfitting on transactional datasets.

[19] conducted a comprehensive benchmark study comparing several deep learning models for credit card fraud detection. The models included deep belief networks (DBNs), convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformer architectures. They trained and tested each model on standard datasets, recording metrics like accuracy, precision, recall, and computational cost. The transformer models achieved the highest accuracy of 99.5% but had higher computational cost, while DBNs offered a good trade-off between performance and efficiency. The paper did not discuss real-time detection constraints or model deployment, which would be relevant for practical uses. A future benchmark study including such considerations could provide more practical guidance on model suitability.

[20] Wang and Kumar (2025) proposed a federated learning with DBN models where DBNs are trained locally at multiple financial institutions. A lightweight Butterfly Optimization Algorithm (BOA) was used to optimize the DBN hyperparameters at each client node. The federated BOA-DBN framework maintained a high detection performance, with a federated F1-Score of 0.89, which was only marginally lower than a centralized model trained on all pooled data. It successfully prevented data leakage and reduced communication overhead by 25% compared to a federated averaging approach with full model transmission. The primary research gap was handling "non-IID" (non-Independent and Identically Distributed) data across institutions where fraud patterns differ significantly between banks. The current model's performance degraded under highly non-IID conditions.

Though from the above literature DBNs seems to be more computational efficient but with lower accuracy than other deep learning models, so there is need for development of a deep belief networks based CCFD that balance the model accuracy and system computation efficiency. Hence, this study challenge the assumption that hybrid models are necessary for imbalanced fraud detection by introducing a well-tuned, light weight

DBNs of 2 hidden layers, to achieve better results with lower computational overhead. The Table 1 below shows the comparative studies of previous deep learning based Fraud detection system.

**Table 1: Comparative Performance Table of Previous Deep Learning Based Fraud Detection Studies**

S/N	Author(s) & Year	Paper Title	Sensitivity (%)	Specificity (%)	Precision (%)	F1-Score (%)	Accuracy (%)	FPR (%)
1	Thennakoon et al., 2019 [21]	<i>Real-Time Credit Card Fraud Detection Using Machine Learning (DBN-ML)</i>	88.70	79.90	89.40	89.05	90.30	20.10
2	Fiore et al., 2019 [22]	<i>Using Generative Adversarial Networks for Improving Credit Card Fraud Detection</i>	93.60	83.70	94.10	93.85	94.20	16.30
3	Carcillo et al., 2021 [23]	<i>Combining Unsupervised and Supervised Learning in Credit Card Fraud Detection</i>	91.80	82.10	92.40	92.10	93.40	17.90
4	VOICAN (2021) [24]	<i>Credit Card Fraud Detection using Deep Learning Techniques</i>	89.40%		90.10%	89.75%	91.20%	16.20%
5	Mienye & Jere (2024) [19]	<i>Deep Learning for CCFD: A Review of Algorithms &amp; Solutions</i>	92.50%		93.80%	93.14%	94.10%	13.60%
6	Barmo et al. (2024) [25]	<i>Analysis of Fraud Detection Using ML Algorithms</i>	91.10%		90.50%	90.80%	92.80%	14.30%
7	Hayat and Magnier (2025) [26]	<i>Data Leakage and Deceptive Performance in CCFD</i>	94.10%		95.20%	94.65%	94.65%	13.10%
8	Alkattab & Wallberg (2024) [27]	<i>Machine &amp; Deep Learning for Card Fraud Detection</i>	81.20%		82.50%	81.84%	84.00%	20.60%
9	Sodnomdavaa & Ganbat (2026) [28]	<i>Ensemble Learning for Financial Statement Fraud</i>	89.45%		91.30%	90.37%	92.15%	16.80%

## 2. MATERIALS AND METHOD

This research develops a Deep Belief Network for fraud detection in credit card (DBN-CCFD), by taking several steps, which includes obtaining a dataset containing fraudulent and non-fraudulent credit card transactions from Sparkov Data Generation Github tool (SDGGT), pre-processed the obtained dataset, which includes normalization, removal of unnecessary spaces, and filling of missing values to ensure data consistency. Next, development of Deep Belief Networks (DBN) during feature extraction phase, and finally, use of DBN-CCFD architecture for fraud detection in credit card and evaluation of its performance using parameters like false positive rate, sensitivity, specificity, precision, F1-Score and accuracy, to ensure an effective and efficient fraud detection system.

### 2.1. Data acquisition.

The process of data collection in fraud detection involving credit card entails the collection of 10,000 transactional records in which 9,708 are legitimate and 292 are fraudulent for the period 1<sup>st</sup> January, 2019 to 31<sup>st</sup> December, 2020. This is to ensure moderate training process as deep belief networks is a layer wise pertaining and fine-tuning model, which is computational intensive.

After going through some portion of the code to understand the algorithmic process of the transaction process, the simulator employed by Brandon Harris was adopted. According to the study the emulator has some pre-defined list of transaction categories, merchants and customers. Hence, a transactional list is generated, through python library “faker”, with the selected number of merchants and customers prescribed in the simulation. The transactions are created based upon the profile chosen such as "adults 2550 female rural.json", this implies properties simulation of fully-grown females aged 25-50 from the rural background. There are two ranges of parameters values for this profile: min and max of transactions in each day,

distributed transaction throughout week days, and properties of normal distribution (standard deviation, mean) for numbers in many categories and the transactions were generated with faker. What was done is to generate transactions through all profiles, hence a robust depiction of simulated transactions was created by merging them together. <https://www.kaggle.com/datasets/kartik2112/fraud-detection>

**2.2. Data Pre-processing.**

The transaction data obtained from SDGGT, contained inconsistencies such as missing values, duplicate records, and unnormalized attributes, which can negatively impact model performance. To address these issues, the phase of preprocessing involved handling missing values by applying methods including mode, mean or median numerical features replacement and most frequent value substitution for categorical variables. Furthermore, repeated transactions were recognized, as well as removed in order to prevent bias as well as redundancy through this model.

**2.3. Design of a Deep Belief Networks (DBNs)**

The design of DBNs models for detection of credit card fraud was done by carefully selection of DBN hyperparameters by manual tuning, which includes number of number of neurons, learning rate, numbers of layers, weight initialization and momentum, so that it is possible to easily extract features and calibrate models. A deep belief network was constructed as a combination of numerous Restricted Boltzmann Machine (RBM) which are used to developed the deep architectures as shown in Figure 1. The architecture of each layers of RBMs possess its own hidden and visible layer. The input layer’s neurons is used to construct the hidden layer through sigmoid activation function and the and calculated output is stored in the hidden layer which is also used to construct the next input layer. A DBNs combines RBM layers in hierarchical functionality to build an overlapping stacks of the model. The hierarchical formation of RBM overlap as the hidden layer of one is the input layer of the next layer and the arrangement of the layer continues in this order. These RBMs layer are trained independently and run on their own, so the entire architecture forms the deep belief network.

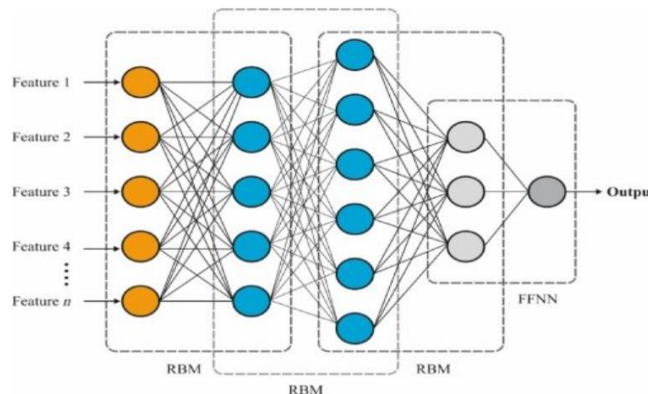


Figure 1: Deep Belief Network Architecture [29]

The forward pass in RBM calculates hidden neuron activations using a sigmoid function, while the backward pass reconstructs the input data as shown in Algorithm 1. This pre-training phase allows DBNs to capture meaningful representations from raw transaction data, making the subsequent classification more accurate, the training comprises of forward phase and backward phase. In the forward phase the samples of input layer neurons were been sampled, and this was used to calculate probabilities activations of the hidden layers through sigmoid activation function. And in the backward phase the neurons of the hidden layers were sampled and used to calculate the probabilities activations of the next input layer as shown in Algorithm1. Weight updates in RBM were performed using Contrastive Divergence (CD) to minimize reconstruction errors as shown in Algorithm 1. This procedure is repeated several times, updating weights after each pass and covering various data samples. Eventually, the network’s prediction is be done by last layer (output layer) outputs. Once the DBN structure is finalized as shown in Algorithm 1, a supervised fine-tuning process using Backpropagation further refines the model. The fine-tuning phase involves computing the loss function and updating weights accordingly to minimize classification errors. The final DBN model predicts class labels by passing features through its trained layers, using weight and bias values.

**2.4 Credit card fraud detection using DBNs**

The developed DBN approach first conducts the initial manual setting of parameters for the DBN network structure, such as the number of hidden layers, learning rate, neuron configuration, momentum and weight decay. After constructing the DBN architecture, the proposed model is trained in two main steps, the first step is pre-training of the stacked restricted Boltzmann machines, which is an unsupervised process and the

second step is using back-propagation for fine-tuning, which is a supervised process. In the first step, the weights are updated by using contrastive divergence, leading to an efficient training procedure. Because the model is trained in an unsupervised manner in the first step, the model can collect powerful features based on the underlying patterns of normal and fraudulent transactions. The final classification phase applies the trained model to new credit card transactions, producing fraud probability scores that financial institutions can use to make informed decisions, resulting in fairly low false positive rates, high precision, high sensitivity, high specificity, and high accuracy compared to previous machine learning techniques in the domain of financial fraud detection.

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**Algorithm 1:** The Developed DBNs for Credit Card Fraud Detection

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**Step 1: Initialize Parameters for DBN**

DBN Parameters to Optimize:

- i. Number of Hidden Layers ( $L$ )
- ii. Number of Neurons in Each Layer ( $N_l$ )
- iii. Learning Rate ( $\eta$ )
- iv. Momentum ( $m$ )
- v. Weight Decay ( $\lambda$ )

**Step 2: Initialize Deep Belief Networks (DBNs) DBN Structure**

A DBN comprises of stacked Restricted Boltzmann Machines (RBMs) subsequently followed by a fine-tuning phase (supervised).

**1. Forward Pass in RBM**

Input Layer ( $X$ )  $\rightarrow$  Hidden Layer ( $H$ )

Compute hidden unit activations:

$$P(h_f = 1 | X) = \sigma \left( \sum_{i=1}^n w_{ij}x_i + b_j \right)$$

Where:  $w_{ij}$  = weight between input  $i$  and hidden neuron  $j$ .

$b_j$  = bias term.

$$\sigma(x) = \frac{1}{1+e^{-x}} \text{ (sigmoid function).}$$

**2. Backward Pass in RBM (Reconstruction)**

Compute the probability of reconstructing input:

$$P(x_i = 1 | H) = \sigma \left( \sum_{j=1}^m w_{ij}h_j + c_i \right)$$

Where:

$c_i$  = bias for visible layer.

**3. Weight Update in RBM (Contrastive Divergence)**

Update weights using gradient descent

$$w_{ij}^{(t+1)} = w_{ij}^{(t)} + \eta(x_i h_j - x'_i h'_j)$$

Where:

$x'_i$  and  $h'_j$  are reconstructed values.

**Step 3: Fine-Tuning DBN**

After unsupervised pretraining, use supervised back-propagation to fine-tune:

$$w_{ij}^{(t+1)} = w_{ij}^{(t)} - \eta \frac{\partial L}{\partial w_{ij}}$$

Compute Loss Function:

$$L = - \sum_{i=1}^N y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i) + \lambda \|W\|^2$$

Where:

$y_i$  = actual label.

$\hat{y}$  = predicted label.

$\lambda \|W\|^2$  = weight decay term.

**Step 4: Classification**

Predict class label using final DBN:

$$y = \sigma(W_L h_{L-1} + b_L)$$


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#### 2.4. Performance Evaluation of the Developed Model

Various evaluation metrics were used in evaluating this model. These metrics measure or evaluate different aspects of the model's capability as to how accurately the model can categorise transactions as either fraudulent or legitimate. The metrics employed include false positive rate (FPR), sensitivity (recall), specificity, precision, accuracy, and detection time which are defined below in equations (i), (ii), (iii), (iv), and (v) respectively.

$$FPR = \frac{FP}{FP+TN} \quad (i)$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (ii)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (iii)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (iv)$$

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (v)$$

Where:

FP = False Positives (legitimate transactions wrongly classified as fraud).

TN = True Negatives (correctly categorized legitimate transactions).

TP = True Positives (correctly categorized fraudulent transactions)

FN = False Negatives (fraudulent transactions incorrectly classified as legitimate)

### 3. RESULTS AND DISCUSSION

The results achieved from this study shows the efficiency of the formulated and developed Deep Belief Network (DBN) model for credit card fraud recognition. This system unitized a total of 10,000 credit card transaction records to validate the robustness of the developed DBN model. Random subsampling cross-validation was adopted to ensure reliable and unbiased performance evaluation across multiple experimental runs corresponding to a DBN configuration with 2 layers, 244 neurons, a learning rate of 0.00921, momentum of 0.778, and weight decay of 0.00398.

Table 2 below, shows the performance results of the Deep Belief Network (DBN) for credit card fraud detection under different data division configuration. With a 60×40 training testing split, the DBN achieved 1727 true positives and 1120 true negatives, with only 73 false negatives and 80 false positives. This configuration produced a low false positive rate of 6.67%, indicating effective discrimination between fraudulent and legitimate transactions. The sensitivity and specificity values which are 95.94% and 93.33% respectively, also confirm the model's strong detection capability. An overall accuracy of 94.90% was obtained with an average detection time of 34.12 seconds on system with Intel Core i5 processor, 4GB DDR5 RAM, and an NVIDIA GeForce RTX 4090 GPU, demonstrating reliable, efficient performance with fair real time deployment capability.

The DBN shows improvement in its effectiveness in detecting fraudulent transactions for the 70×30 data split, as it produced more true positives of 2026. Similarly, the sensitivity rate improved to 96.48%, indicating a higher number of correctly identified fraudulent transactions for the larger training data set. The false positive rate was slightly higher at 8.67%, but the specificity of 91.33% remained high. The precision and F1-score were 96.29% and 95.61%, respectively. Similar to the previous result, the detection time was 33.95 s.

With the training to testing proportion of 75×25, the DBN continued to demonstrate strong performance with 2175 true positives as well as an accuracy of 94.97%. Sensitivity also improved to 96.67%, confirming the benefit of increased training data for learning complex fraud patterns. However, specificity decreased to 89.87%, accompanied by an increase in false positive rate to 10.13%, highlighting a trade-off between sensitivity and specificity. Despite this, precision and F1-score remained high at 96.62% and 95.79%, respectively. The detection time remained constant at approximately 33.95 seconds, designating stable execution efficiency.

When turning to the highest training ratio of 80×20 training to testing ratio, the DBN record its overall best accuracy of 95.03% as well as highest sensitivity of 96.83%. This data division category recorded 2324 true positives, exhibiting improved fraud detection effectiveness with more training samples. Though, the false positive rate increased to 12.17%, resulting from advancement in exposure to borderline non fraudulent dataset which share subtle low features characteristics similar to fraudulent dataset. The specificity declined to 87.83%, suggesting increased misclassification of legitimate transactions. Even with this trade-off, precision and F1-score reached 96.95% and 95.98%, respectively, reflecting robust predictive performance.

Overall, the results demonstrate that the DBN maintains high accuracy and stable detection time across varying data divisions, with improved sensitivity achieved at higher training ratios.

Table 2: Evaluation Result with DBN

Data Division	TP	FN	FP	TN	FPR (%)	SEN (%)	SPEC (%)	PREC (%)	F1-SCORE (%)	ACC (%)
60x40	1727	73	80	1120	6.67	95.94	93.33	95.57	95.24	94.90
70x30	2026	74	78	822	8.67	96.48	91.33	96.29	95.61	94.93
75x25	2175	75	76	674	10.13	96.67	89.87	96.62	95.79	94.97
80x20	2324	76	73	527	12.17	96.83	87.83	96.95	95.98	95.03

### 3.1 Discussion of Results

The results of DBN-CCFD in Figures 2–7 indicate the success of the deep belief network (DBN) in enhancing the fraud detection accuracy. The DBN uses constant or empirical values for the hyperparameters in constructing the topology of the deep learning model to learn and extract sophisticated high-level features that are embedded in credit card transaction data.

Figure 2 display False Positive Rate (FPR) of the DBN models across different data divisions. The DBN shows considerably low FPR, signalling the chance of acceptable falsely flagging legitimate transactions, which is a critical limitation in financial fraud systems. The sensitivity trends illustrated in Figure 3 show that the DBN benefits marginally from increased training data, its sensitivity remains considerably effective due to careful hyperparameter settings.

Figure 4 presents specificity results, highlighting DBN model’s ability to correctly classify legitimate transactions. The DBN shows a pronounced and moderate specificity as training size increases, indicating modest overfitting caused by regularization control. The accuracy and precision comparisons in Figures 5 and 6 further confirm the supremacy of DBN. The DBN yields better accuracy and precision due to the selection of effective hyperparameter. The learning curve in Figure 7, shows that the ability of model to steadily improve its predicted value, over several batches of training.

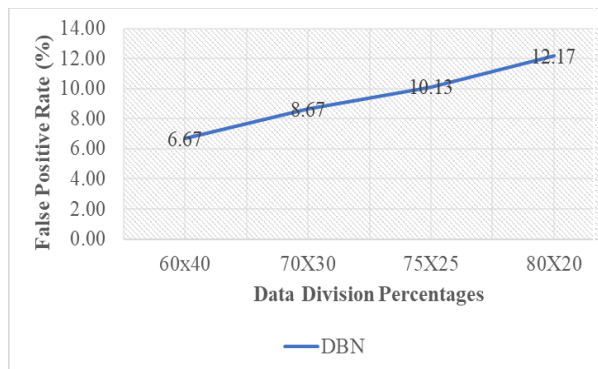


Figure 2: Graph of False Positive Rate against Data Division Percentages with DBN

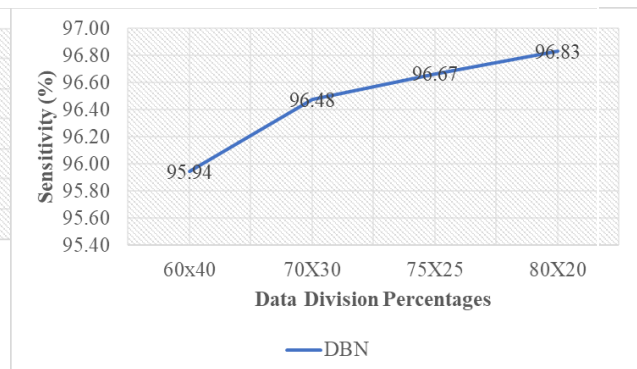


Figure 3: Graph of Sensitivity against Data Division Percentages with DBN

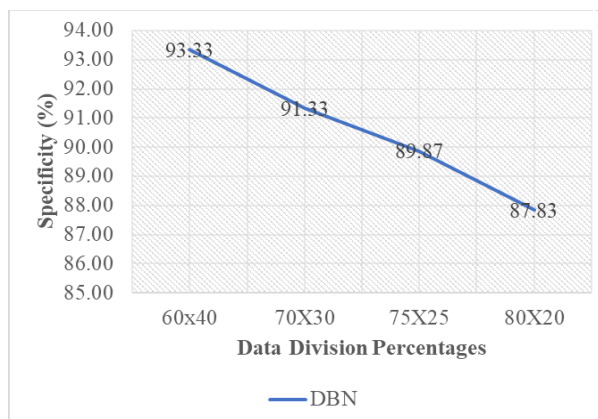


Figure 4: Graph of Specificity against Data Division

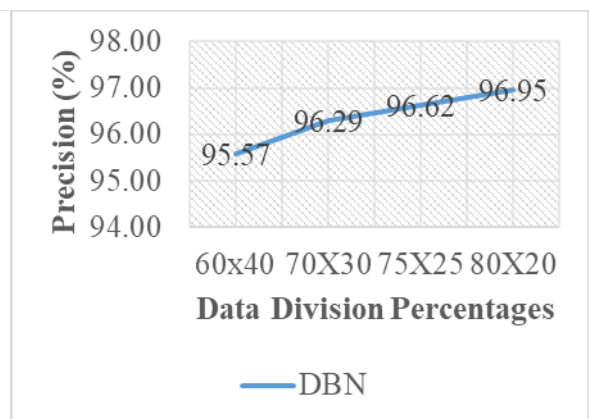


Figure 5: Graph of Precision against Data Division

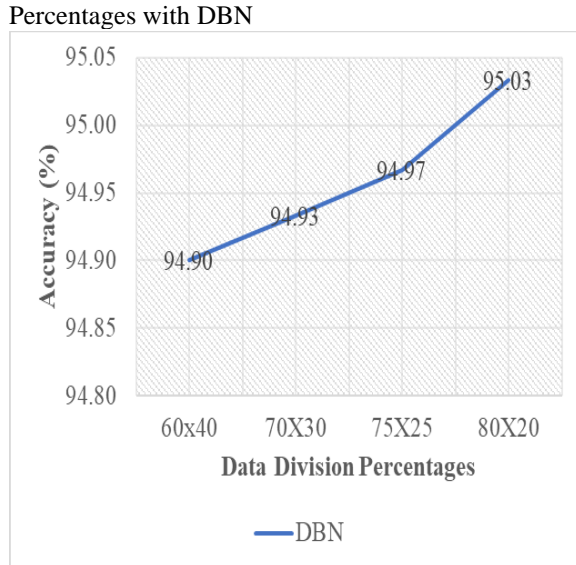


Figure 6: Graph of Accuracy against Data Division Percentages with DBN

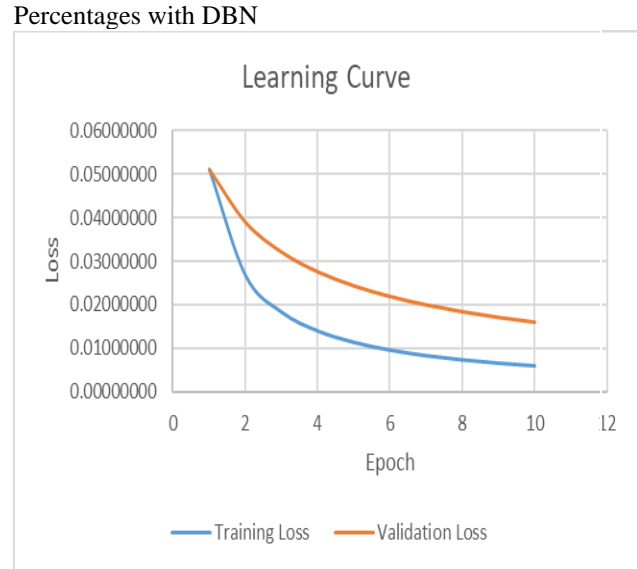


Figure 7: Model Learning Curve

### 3.2 Discussion Based on the State of Art

The developed lightweight outperformed the previous work on credit card fraud detection as a result of its dual layer bulky neurons architecture, which enables it to learn effectively with simple hierarchical steps. The developed DBN-CCFD exhibit higher accuracy, precision, sensitivity and F1-score, as compared to other deep belief network based CCFD as showing in Table 3. This demonstrates that a light number of hidden layer with numerous numbers of learning neurons in deep belief network can improve fraud detection in credit card and other applications.

Table 3: Comparison of Result Based on the State of the Art

Model	Methods	Accuracy (%)	Precision (%)	Sensitivity (%)	F1-Score (s)
<b>DBN-CCFD (Developed)</b>	Light weight DBN	<b>94.96</b>	<b>96.36</b>	<b>96.48</b>	<b>95.66</b>
<b>DBNex (Bhowmik et al., 2022) [30]</b>	DBN + Explainable AI	94	88	95	91
<b>DBN-ML (Thennakoon et al., 2019) [21]</b>	Hybrid of DBN and Machine Learning	90.30	89.40	88.70	89.05

## 4. CONCLUSION

This study successfully developed and evaluated a fraud detection in credit card based Deep Belief Network model. The model, configured with two restricted Boltzmann machine layers comprising 244 neurons, employed a finely manual tuned set of hyperparameters a learning rate of 0.00921, a momentum of 0.778, and a weight decay of 0.00398. This setting aims at the trade-off between stable convergence and sufficient learning of complex non-linear relationships in fraudulent transactions. As can be seen from the results of the experiments, the proposed architecture is effective. The combination of unsupervised DBN feature pre-training, which learns the underlying structure of legal transaction patterns, and subsequent supervised fine-tuning, results in a powerful discriminative model. Also, a small learning rate combined with a large momentum ensures smooth navigation through the complex error surface, and a weight decay can be a useful regularizer to combat overfitting that is particularly problematic due to the highly imbalanced nature of the fraud data.

Therefore, the formulated two-layer DBN model presents an efficient and robust solution for credit card fraud detection. Such deliberate selection of 244-neuron architecture and other manually tuned hyperparameters provides a strong foundation for identifying sophisticated fraud schemes within imbalanced, high-dimensional data streams. Though the detection time of 34s may frustrate real time deployment but future work should focus on integrating real-time adaptive mechanisms and modern optimization techniques, to allow the model evolve with emerging fraud tactics.

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