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Walrus Optimized Deep Belief Network for Credit Card Fraud Detection

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ABSTRACT

Detection of fraud in credit cards (CCFD) has become a critical research area as financial losses continue to increase annually. The traditional rule-based and conventional machine learning model struggles to address the challenges of concept drift and an imbalanced dataset. While deep belief network (DBN) algorithms can learn highly complex features, they require meticulous hyperparameter tuning, which can lead to suboptimal convergence. Hence, this study employs walrus optimization algorithm to automate the DBNs hyperparameters. Ten thousand (10,000) of the imbalance dataset containing 3000 fraudulent and 6000 non-fraudulent transactional datasets were obtained and pre-processed using imputation, min-max, and one-hot encoding techniques. The DBNs were developed as a stack of Restricted Boltzmann Machines (RBMs). The optimised DBNs (WOA-DBNs) were then developed and applied to credit card fraud detection, with data divided 60:40, 70:30, 75:25, and 80:20 (train: test), generated randomly. The implementation was performed using MATLAB 2023a. The performance of DBN-CCFD was evaluated and compared with the performance of WOA-DBN-CCFD. At the highest training ratio of 80:20, WOA-DBN-CCFD shows False Positive Rate (FPR), sensitivity, specificity, precision, F1-Score, accuracy and detection time of 8.25%, 97.81%, 91.75%, 97.93%, 97.87%, 96.60% and 26.01s as against DBN-CCFD of 12.25%, 96.81%, 87.75%, 96.93%, 96.87%, 95.00% and 33.97s respectively. This performance metric indicates that the developed WOA-DBN-CCFD shows modestly better performance in credit card fraud detection, with lower FPR and detection time, while maintaining higher values on other metrics.

INTRODUCTION

The process of Fraud Detection involves identifying and preventing malicious attacks by monitoring user activities, including fraud, intrusion attempts, and payment defaults. This issue is highly relevant to fields such as machine learning and data science, where automated solutions are critical (Kou *et al.*, 2021).

The level of credit card fraud is now a serious issue for banks and the financial industry due to the increasing number of fraudulent transactions (Alpaydin, 2021). With increased use of digital banking and e-commerce, cybercriminals have found new ways to exploit vulnerabilities in payment systems (Zhang *et al.,* 2018). Credit card fraud remains a pervasive threat to global financial systems, with losses estimated to surpass $40 billion annually by 2027. Traditional rule-based fraud detection methods often fail to keep up with evolving fraud techniques (West and Bhattacharya, 2016; Olagunju *et al,* 2025). Hence, financial institutions are now adopting machine learning and artificial intelligence to improve fraud detection systems (Nguyen and Huh, 2022). These technologies help identify suspicious patterns and mitigate misclassification in fraud detection.

Machine learning-based fraud detection models rely on historical transaction data in discriminating between fraudulent and legitimate activities (Patel and Shah, 2019). Supervised learning models, including support vector machines, random forests, decision trees, and neural networks, all confirmed high accuracy in detecting fraudulent transactions (Liu *et al.,* 2021). Furthermore, unsupervised learning model, including anomaly detection and clustering, were used to recognise previously unknown fraud patterns (Bolton and Hand, 2002). However, cybercriminals continually adapt their strategies, necessitating that fraud detection models be regularly updated (Bhattacharyya *et al.,* 2011). A combination of supervised and unsupervised models is often used to enhance fraud detection efficiency, because single machine learning classifiers struggle to address the inherent challenges of imbalanced datasets, concept Drift, real-time detection and Feature Engineering (Dal-Pozzolo *et al.,* 2015).

The Deep learning models have materialised as better alternatives, in which they possess the capability to automatically extract complex features from large transaction datasets (Liu *et al.*, 2021; Oguntoye et al., 2023). These methods, including deep belief networks, convolutional neural networks, and recurrent neural networks, have shown superior performance in detecting fraudulent transactions (Goodfellow *et al.*, 2016). The effectiveness of deep learning lies in its ability to analyse serial financial data and recognise hidden fraud patterns that traditional methods may miss (Atanda *et al.* 2023).

Among deep learning Techniques, deep belief networks (DBNs) have shown promising results in detecting fraud in credit card systems due to their hierarchical learning structure (Hinton et al., 2006). DBNs are constructed by combining layers of restricted Boltzmann machines, which can extract abstract representations from the dataset (Bengio, 2009). Such deep architectures enable DBNs to learn highly complex relationships among transaction features, ensuring their effectiveness in fraud detection (Ding et al., 2020). In contrast to machine learning techniques, DBNs can capture feature representations without explicit feature engineering (Zhai et al., 2018). As a result, they provide higher accuracy as well as generalization in recognising deceitful transactions.

The future of credit card fraud detection lies in integrating advanced deep learning techniques, such as DBNs, into real-time transaction monitoring systems (Pham *et al.,* 2022). While Deep Belief Networks (DBNs) have demonstrated superior performance in detecting non-linear, low-frequency fraud patterns and possess ability to autonomously extract high-level features from raw transactional data (Ghosh and Reilly, 2021). Their adoption is hindered by critical limitations, which include high computational costs during training due to multi-layer architectures, the requirement of manual meticulous hyperparameter tuning (such as learning rates, layer sizes), which often leads to suboptimal convergence, and overfitting on imbalanced datasets (Ghasemi *et al.,* 2018; Sethi *et al.,* 2023). These challenges limit their scalability and real-world applicability, necessitating advanced optimization techniques to enhance performance (Ogundepo et al., 2022; Oguntoye *et al*., 2025).

Rajalakshmi *et al.* (2026) present an enhanced Quantum deep belief network employed for financial fraud detection. This study compares 3-layer DBN configurations on the Credit Card Fraud Detection dataset: 1 Quantum DBN (1 QRBM layer), 2 Quantum DBN (2 QRBM layers), and a full Quantum DBN (all QRBM layers). Models were trained via contrastive divergence and assessed using precision, recall, and F1-score. Results from this work show the full Quantum DBN outperforming others with a precision of 0.581, a recall of 0.637, and an F1-score of 0.602, yielding a 34.4% F1 improvement over the classical DBN (precision of 0.319, a recall of 0.755, and an F1 of 0.448). But despite improvements, the absolute precision of 58% remains low for real-world deployment.

Kafhali *et al,* (2024) developed an optimized deep learning approach for detecting fraudulent transactions. An intelligent system for detecting fraudulent transactions was proposed, using various deep learning architectures, including artificial neural networks (ANNs), recurrent neural networks (RNNs), and long short-term memory (LSTM), with a Bayesian optimisation algorithm for hyperparameter tuning. The RNN architecture demonstrated better efficiency and yielded better results in a shorter computational time than ANN or LSTM architectures by achieving the best accuracy score of 95.93%, while the ANN architecture achieved the second-best score of 89.93%, with LSTM recording the lowest score of 75.62%, showing that the RNN architecture outperforms the other deep learning models in classifying fraud. But the problem of suboptimal solution still persists in this system, thereby keeping higher accuracy at 95.93%.

Reddy *et al.* 2024 worked on Deep learning-based credit card fraud detection in federated learning. In this study, the Jellyfish Namib Beetle Optimisation Algorithm-SpinalNet (JNBO-SpinalNet) is designed for detecting fraudulent credit card transactions. The classifier's detection process is improved by tuning SpinalNet using the designed JNBO model. The JNBO-SpinalNet model recorded higher performance with 89.10 % accuracy, 13.16 % loss function, 28.68 % Mean Squared Error (MSE), 10.20 % False Positive Rate (FPR), 89.82 % Mean Average Precision (MAP), and 53.56 % Root Mean Squared Error (RMSE). But this model suffers from a high FPR (greater than 9.5%) and poor accuracy, while its computational complexity increases detection time.

Albalawi and Dardouri (2025) enhance credit card fraud detection using deep learning models by mitigating class imbalance. This research evaluates logistic regression, decision trees, and random forests on real-world credit card datasets. A deep learning model incorporating focal loss was developed to further improve detection performance, while the Synthetic Minority Over-Sampling Technique (SMOTE) was applied to mitigate class imbalance. Experimental results show that the improved deep learning model achieved an accuracy of 99.89%, an F1 score of 88.89% and a precision of 80.0%. This result shows that the problem of overfitting on an imbalanced dataset has not been adequately resolved, and suboptimal solutions persist.

The Walrus Optimisation Algorithm (WOA) provides a bio-inspired framework to automate hyperparameter tuning by mathematically modelling the three stages of walruses' lifestyle: Feeding (exploration), Migration (diversity maintenance), and fighting against predators (exploitation). By optimising DBN parameters such as learning rates, regularisation terms, and layer configurations, WOA can reduce training time, mitigate overfitting on an imbalanced dataset, prevent suboptimal solutions, and enhance detection accuracy (Zhang *et al.,* 2024).

METHODS

This research develops and evaluates the Walrus-Optimized Deep Belief Network (WOA-DBN) for credit card fraud detection. Numerous important steps were being undertaken. First, there is the collection of a dataset including fraudulent and non-fraudulent transactions. Next, there is the pre-processing of the collected dataset. Following this, a Walrus Optimisation Algorithm (WOA) was developed. This WOA was then applied to select the optimal hyperparameters for Deep Belief Networks (DBNs) during the feature extraction phase. Finally, the WOA-DBNs model was integrated into credit card fraud detection, and performance evaluation metrics such as false positive rate, sensitivity, specificity, precision, F1-score, accuracy, detection time, and processing time were employed to ensure the robustness and efficiency of the fraud detection system, as shown in Figure 1.

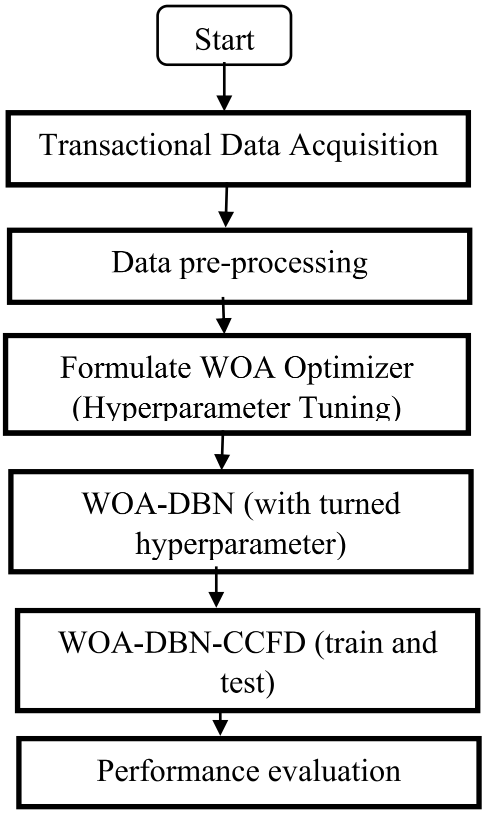

Figure 1: Structure of WOA-DBN-CCFD

Data Acquisition

The data for credit card fraud detection was acquired from transactional records of a simulated credit card dataset, covering non-fraudulent and fraudulent transactions from 1st January 2019 to 31st December 2020. It contains 1000 customers and credit cards from a pool of 800 merchants, while a ten-thousand (10,000) dataset containing 3000 fraudulent and 6000 non-fraudulent transactions was obtained.

Data pre-processing

The transaction data contained inconsistencies, including missing values, duplicate records, and unnormalized attributes, which can negatively impact model performance. To address these issues, the preprocessing phase involved handling missing values using imputation methods such as the mean to replace missing values between two known features, and the median or mode for numerical replacement of definite feature patterns. Furthermore, repeated transactions were identified and removed using a rule-based system that compares similar transactional features via feature rules to prevent bias and redundancy within the model. While normalisation of features like transaction amount, account balance, and transaction time, which have varying scales, was done by using min-max scaling techniques to standardise values, ensuring that the model does not assign undue importance to features of larger value. Categorical features such as transaction type, merchant location, and cardholder category were also transformed into numerical representations for model compatibility using one-hot encoding.

Walrus-Optimization Algorithm (Hyperparameter Tuner)

The deep belief network hyperparameters, including the number of layers, the number of neurons, the learning rate, the momentum, and the weight decay, were optimised using walrus optimisation techniques. The best or strongest solution is being updated in three stages, which are the exploration stage, as shown in equations (1) and (2), the diversity maintenance stage, as shown in equations (3 and (4) and the exploration stage, as shown in equations (5) and (6). This update continues within the specified repetition until the optimum value is reached.

$$x_{i,j}^{p_1} = x_{i,j} + rand_{i,j} \cdot \left(SW_j - I_{i,j} \cdot x_{i,j}\right) \quad (1)$$

$$X_i = \begin{cases} x_i^{p_1}, F_i^{p_1} < F_i, \\ X_i, else \end{cases} \quad (2)$$

$$x_{i,j}^{p_2} = \begin{cases} x_{i,j} + rand_{i,j} \cdot \left(x_{k,j} - I_{i,j} \cdot x_{i,j}\right), \; F_k < F_i, \\ x_{i,j} + rand_{i,j} \cdot \left(x_{i,j} - x_{k,j}\right), \quad else, \end{cases} \quad (3)$$

$$X_i = \begin{cases} x_i^{p_2}, F_i^{p_2} < F_i \\ X_i, \; else \end{cases}, \quad (4)$$

$$x_{i,j}^{p_3} = x_{i,j} + (lb_{local,j}^{t} + (ub_{local,j}^{t} - rand \cdot lb_{local,j}^{t})) \quad (5)$$

$$X_i = \begin{cases} x_i^{p_3}, F_i^{p_3} < F_i \\ X_i, \; else \end{cases}, \quad (6)$$

Where, $x_i^{p_1}$, $x_{i,j}^{p_2}$, and $x_{i,j}^{p_3}$ are new solutions generated by the exploration, diversity maintenance, and exploitation stages, respectively. $F_i^{p_1}$, $F_i^{p_2}$ and $F_i^{p_3}$ are the objective function values of the three stages. $rand_{i,j}$ exist as random figures having a range interval [0, 1], SW remains the best walrus possessing the finest value with regard to the objective function, also $I_{i,j}$ remain random integers carefully chosen in the range from 1 to 2. $lb_{local,j}^{t}$ and $ub_{local,j}^{t}$ are bottom and top bounds acceptable for the hyperparameter variables.

Walrus Optimized deep belief networks

The optimised deep belief networks, formulated as above and using the WOA, enhance credit card fraud detection by improving hyperparameter selection. The WOA algorithm was initialised with a set of DBN hyperparameters as shown in Table 1. After initialising the DBN, the stacked Restricted Boltzmann Machines (RBMs) were pre-trained to extract hierarchical features from transaction data. The forward pass in RBM calculates hidden neuron activations using a sigmoid function as described in equation 7, while the backward pass reconstructs the input data as shown in equation (8). Weight updates in RBM were performed using Contrastive Divergence (CD) to minimize reconstruction errors. Table 1 in Section III shows the initial values of the DBN hyperparameter for the standard DBN and the generated values for the WOA-DBN Model using WOA.

$$\boldsymbol{P\left(h_f = 1 \mid X\right) = \sigma\left(\sum_{i=1}^{n} w_{ij}x_i + b_j\right)} \quad (7)$$

$$\boldsymbol{P\left(x_i = 1 \mid H\right) = \sigma\left(\sum_{j=1}^{m} w_{ij}h_j + c_i\right)} \quad (8)$$

Where: w_{lj} = weight between input i and a hidden neuron j $\boldsymbol{b_j}$ = bias term $\boldsymbol{c_i}$ = Bias for the visible layer

Credit card fraud detection using WOA-DBNs

Once the optimal DBN architecture is established through WOA, the model undergoes a two-phase training process of pre-training (unsupervised) of stacked layers of restricted Boltzmann machines as well as a fine-tuning phase (supervised) through back-propagation. 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.

Implementation of the Developed Model

The implementation of the developed WOA-DBNs for credit card fraud detection was achieved with MATLAB R2023a, utilising the Deep Learning Toolbox, Optimisation Toolbox, and Parallel Computing Toolbox to optimise performance and facilitate the complex computations required. The system configuration for this implementation consists of an Intel Core i9-13900K processor, 64GB of DDR5 RAM, and an NVIDIA GeForce RTX 4090 GPU with 24GB of VRAM, enabling CUDA-based training acceleration.

Performance Evaluation of the Developed Model

Some performance evaluation metrics were used in evaluating this model. These metrics measure different aspects of the model's capability to categorise transactions as either fraudulent or legitimate. The metrics employed include false positive rate (FPR), sensitivity (recall), specificity, precision, accuracy, and detection time (a reference time).

RESULTS AND DISCUSSION

In Table 1, the initialised values of the standard DBN hyperparameters are shown in row 1. These indicate that the standard DBN was developed with a shallow, fixed architecture of 2 hidden layers, 244 neurons, a learning rate of 0.00921, momentum of 0.778, and weight decay of 0.00398. Also, for 30 iterations, the optimal hyperparameter configurations obtained using the Walrus Optimisation Algorithm (WOA) are shown in row 2 of Table 1. This results in an enhanced model, a two-layer architecture with increased neurons, a higher learning rate, and improved momentum, with weight decay settings.

Table 1: Default DBN Hyperparameters and Optimal DBN Hyperparameter Selection with WOA

Techniques	Number of Layers	Number of Neurons	Learning Rate	Momentum	Weight Decay
DBN	2	244	0.00921	0.778	0.00398
WOA-DBN	2	300	0.02331	0.87	0.00111

Table 2: Evaluation Result with DBN

Data Division	TP	FN	FP	TN	FPR (%)	SEN (%)	SPEC (%)	PREC (%)	F1-SCORE (%)	ACC (%)	Time (sec)
60x40	2303	97	107	1493	6.69	95.96	93.31	95.56	95.76	94.90	34.12
70x30	2026	74	78	822	8.67	96.48	91.33	96.29	96.38	94.93	33.95
75x25	1812	63	63	562	10.08	96.64	89.92	96.64	96.64	94.96	33.95
80x20	1549	51	49	351	12.25	96.81	87.75	96.93	96.87	95.00	33.97

Result with DBN

The performance results of the deep belief networks (DBNs) for detecting credit card fraud across different data division ratios are presented in Table 2. Using a 60×40 (4,000) training–testing split, the DBN achieved 2,303 true positives and 1,493 true negatives, with just 97 false negatives and 107 false positives. This configuration produced a low false-positive rate of 6.69%, which is a fair comparative measure between fraud and legitimate transactions. The model has strong detection capability, with sensitivity and specificity values of 95.96% and 93.31%, respectively. Also, the model achieved 34.12s detection time, indicating a fair and effective performance.

From the data division of 70×30 (3,000), DBN has shown an improvement in its fraud detection capability, achieving 2026 true positives and moderately low misclassifications. The sensitivity was amplified to 96.48%, indicating a better ability to make accurate predictions about illegitimate transactions with an increase in the number of training data units. Despite the increase in the false positive rate to approximately 8.67%, the model maintained an extraordinary specificity of 91.33%, with a precision of 96.29% and an F1-score of 95.61%, indicating consistent classification reliability. Also, the 33.95-second detection time achieved indicates a fair computational cost.

But when the training proportion was increased to 75:25 (2,500), the DBN still performed well, achieving 1,812 true positives and 94.96% accuracy. Sensitivity increased to 96.64%, indicating the value of more training data for analyzing complex fraud patterns. Specificity decreased to 89.92%, and the false positive rate increased to 10.08%, suggesting a trade-off between the classification performance on a smaller dataset and the rate of misclassification of legitimate transactions. Yet the precision and F1-score remained high at 96.64% and 96.64%, respectively. The detection time was still around 33.95 seconds, which is a fair estimate.

It achieved the highest overall accuracy at 95.00% and the highest sensitivity at 96.81%, with an average training-to-testing ratio of 80:20 (2,000). This configuration had 1549 false positives, reflecting faster fraud detection with a higher number of training samples. But the false positive rate increased to 12.25%, and the specificity fell to 87.75%, reflecting higher misclassification of legitimate transactions. But the accuracy and F1-score were a compromise: 95.00% and 96.87%, respectively, indicating strong predictive power.

Result with WOA-DBN

Table 3 displays the performance of WOA-DBN across the 60:40 (4,000) split of the training-to-testing dataset, with 2319 true positives, 1508 true negatives, 81 false negatives, and 92 false positives from this split. This resulted in a low false-positive rate of 5.75%, confirming the success of WOA in finding appropriate DBN hyperparameters to reduce the misclassification of legitimate transactions. Also, high sensitivity and specificity, 96.63% and 94.25%, indicate the accurate detection of fraudulent and legitimate transactions. The implementation of the walrus-optimised deep belief network also achieves a high accuracy of 95.93% and computational efficiency, with a detection time of 26.02 seconds.

For the 70:30 (3,000) data division, the WOA-DBN also surpassed the standard DBN-based detection, achieving 2,042 true positives and relatively low misclassifications. Sensitivity increased to 97.24%, indicating better learning from the optimized hyperparameters. The false positive rate fell slightly to 6.89%, but Specificity remained high at 93.11%. The classifier is reliable and balanced with 97.24% sensitivity, 97.05% precision, 96.52% F1-score, 97.05% precision and 96.00% accuracy. The detection time decreased slightly to 25.91 seconds, indicating the efficiency of the optimized DBN.

Increasing the training ratio to 75:25 (2,500) yielded a robust performance for the WOA-DBN, with 1,828 true positives and 96.28% accuracy. Sensitivity increased to 97.49%, indicating that the optimal DBN captures complex fraud patterns as training data increases. The false positive rate rose to 7.36%, but the specificity decreased slightly to 92.64%, suggesting a trade-off between reducing fraudulent data and misclassification. The precision and F1-score remained high at 97.55% and 97.52%, respectively. The time spent in detecting fraud was stable at around 26.05 seconds.

For the 80:20 (2,000) training-to-testing data ratio, which is the largest training data unit, the WOA-DBN demonstrates its overall best accuracy of 96.60% as well as the highest sensitivity of 97.81%. This data division detailed 1565 true positives, which shows the high capacity of optimised deep belief networks to perform fraud detection through automating their hyperparameters by WOA. However, the false positive rate increased to 8.25%, and specificity decreased to 91.75%, suggesting increased sensitivity at the expense of specificity. Even with this trade-off, precision and F1-score values of 97.93% and 97.87% demonstrate consistent and reliable classification performance. Overall, these results confirm that WOA-DBN significantly outperforms the standard DBN by improving accuracy and reducing detection time through effective hyperparameter optimisation.

Table 3: Evaluation Result with WOA-DBN

Data Division	TP	FN	FP	TN	FPR (%)	SEN (%)	SPEC (%)	PREC (%)	F1-SCORE (%)	ACC (%)	Time (sec)
60x40	2319	81	92	1508	5.75	96.63	94.25	96.18	96.40	95.68	26.02
70x30	2042	58	62	838	6.89	97.24	93.11	97.05	97.15	96.00	25.91
75x25	1828	47	46	579	7.36	97.49	92.64	97.55	97.52	96.28	26.05
80x20	1565	35	33	367	8.25	97.81	91.75	97.93	97.87	96.60	26.01

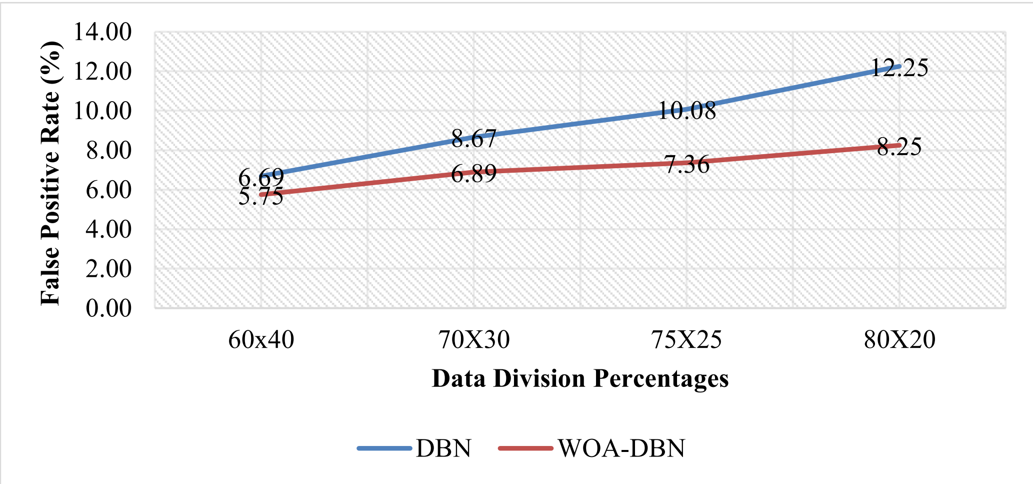

Figure 2: False Positive Rate of each Model

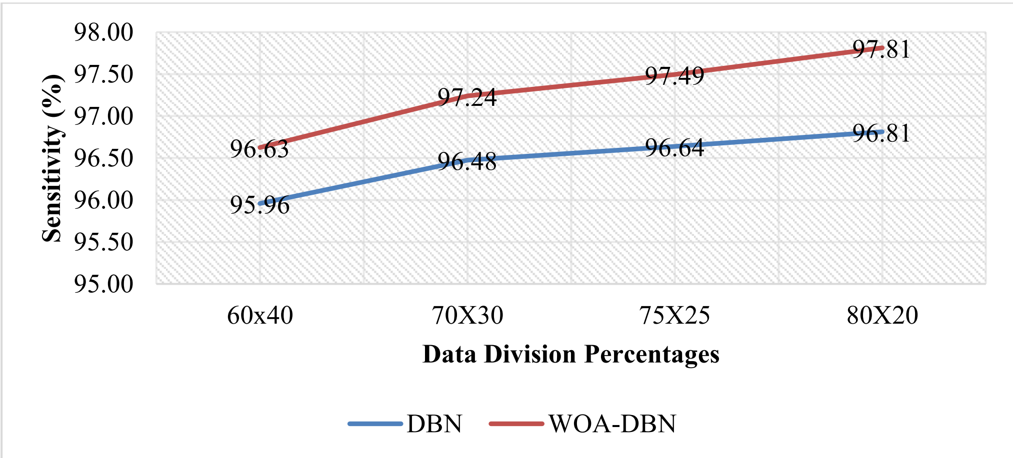

Figure 3: Sensitivity of each Model

Discussion based on Performance Metrics

Figure 2 reports the FPRs of the two models across different data divisions and finds that WOA-DBN consistently reaches the lowest FPR. The FPR on the baseline DBN is higher, so there is a much greater chance that legitimate transactions were misclassified; this is a critical limitation in financial fraud detection mechanisms. The effectiveness of walrus-inspired exploration practices is demonstrated by the WOA-DBN significantly reducing FPR by optimising learning rate, momentum, and weight decay.

In Figure 3, the sensitivity trend shows that WOA-DBN consistently outperforms DBN in detecting fraud. Although DBN's sensitivity increases with training data, it is further limited by the static hyperparameter setting. The WOA-DBN increases sensitivity by optimizing network depth and neuron distribution, thus creating feature abstraction power. Figure 4 shows the specificity results, indicating that each model correctly categorises non-fraudulent transactions. The loss of specificity of the DBN at increasing training size suggests overfitting due to poor control of regularization. The WOA-DBN is more specific because it optimizes weight decay and momentum, thus validating walrus optimization in controlling model complexity.

Figures 5 and 6 show that WOA-DBN is superior in accuracy and precision. The DBN has the lowest accuracy and precision because it cannot optimally adjust learning parameters. WOA-DBN achieves noticeable improvements as optimized learning rates and momentum values lead to better convergence and classification confidence.

Figure 7 compares the average detection time of the two approaches, emphasizing computational efficiency. The DBN records the higher detection time due to inefficient learning caused by non-optimized hyperparameters. WOA-DBN significantly reduces detection time by selecting efficient network configurations and training parameters.

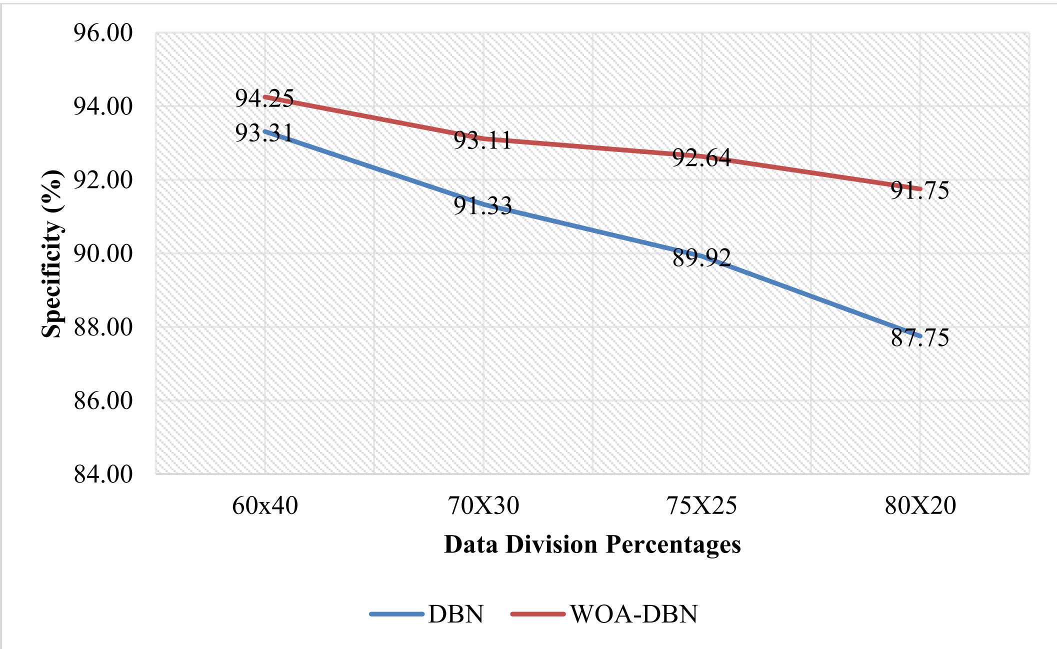

Figure 4: Specificity of each Model

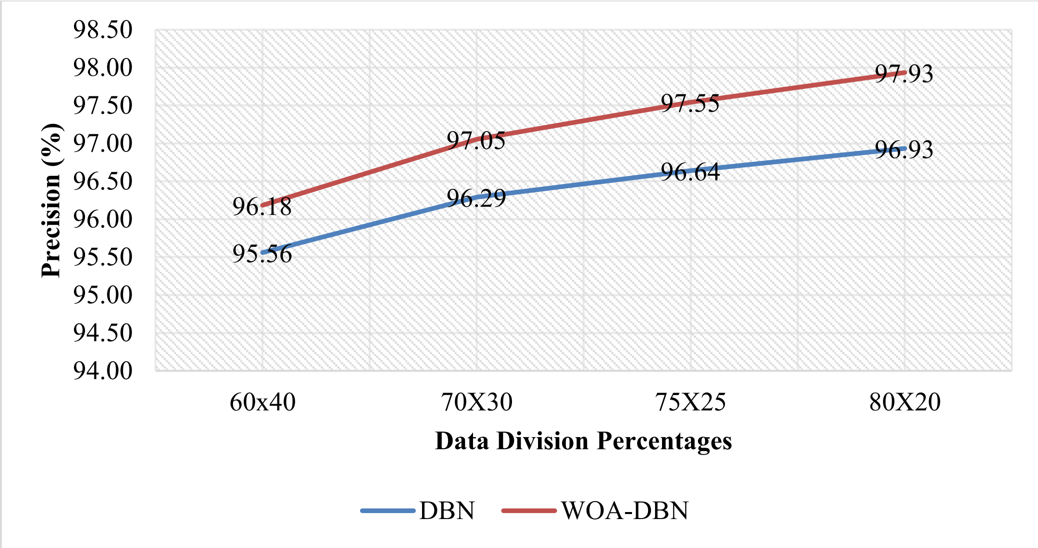

Figure 5: Precision of each Model

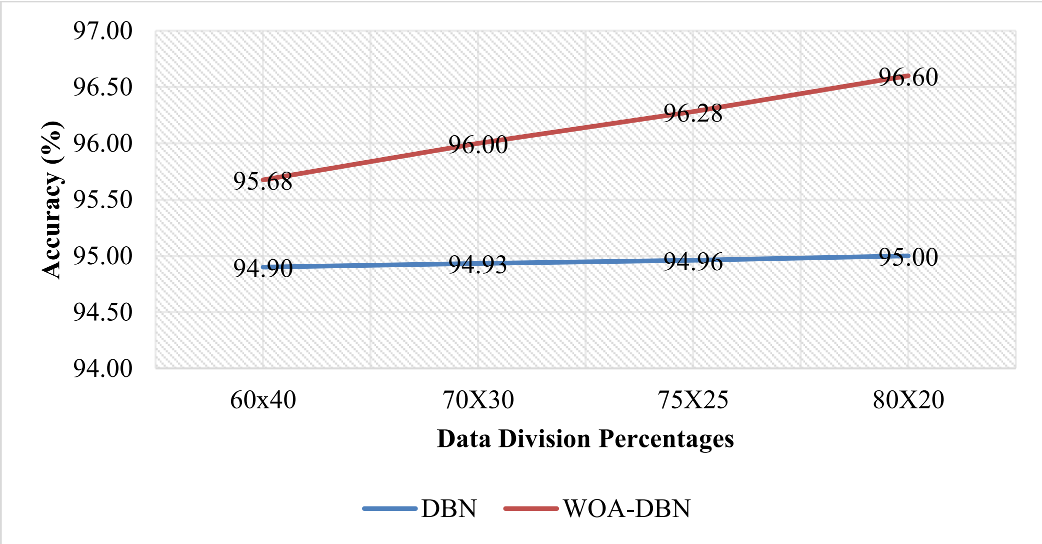

Figure 6: Accuracy of each Model

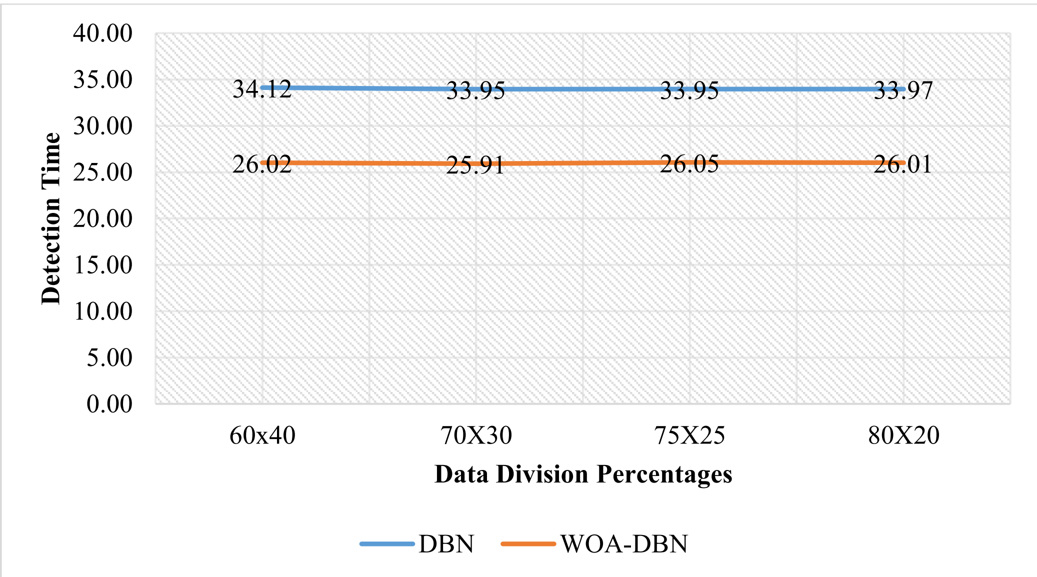

Figure 7: Detection Time of each Model

Discussion based on Comparison with State-of-the-Art Work

The developed WOA-DBN fraud detection system outperformed previous work on credit card fraud detection by applying the walrus optimisation algorithm, which refines the deep belief network model's hyperparameters, thereby enabling it to learn effectively with simple hierarchical steps. The developed WOA-DBN model exhibits higher accuracy, precision, sensitivity, and F1-score compared to other models, as shown in Table 4. This demonstrates that a light number of hidden layers with a large number of learning neurons in a deep belief network can improve fraud detection in credit card and other applications.

Table 4: Comparison of Results Based on the State of the Art

Model	Methods/Techniques	FPR (%)	Sensitivity (%)	Precision (%)	F1-Score (s)	Accuracy (%)
WOA-DBN (Developed)	Walrus Optimization	**7.06**	**97.29**	**97.18**	**97.24**	**96.14**
***Ensemble Learning* (Sodnomdavaa and Ganbat, 2026)**	LSTM, GRU, CNN1D, and Transformer	16.80%	89.45%	91.30%	90.37%	92.15%
***Machine & Deep Learning* (Alkattab and Wallberg, 2024)**	LR, XGB, and DNN	20.60%	81.20%	82.50%	81.84%	84.00%

CONCLUSIONS

This study developed an optimised deep belief network for the detection of credit card fraud by automating the selection of DBN hyperparameters, including learning rate, number of neurons, number of hidden layers, and regularisation constants, to achieve optimal performance. The results from the performance evaluation of the WOA-DBNs versus DBNs for credit card fraud detection show that the walrus-based deep belief network outperformed the standard deep belief network, as the optimised model achieved a lower false positive rate and higher sensitivity, precision, and accuracy. Also, the reduction in fraud detection time achieved by the optimised model made it suitable for a real-time application. This developed model, when deployed, is expected to enhance the efficiency of detecting fraud in the credit card system. Future work can focus on integrating adaptive techniques into the optimisation algorithm to mitigate the effects of evolving credit card fraudster techniques.

Declaration of Competing Interest

There is no conflict of interest among the authors.

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