Toward Efficient Credit Card Fraud Detection: Leveraging Quantum Neural Networks and Modified Feature Selection Techniques

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Abstract – Credit cards are a common form of payment not only because they are extremely convenient to use but also because they are widely accepted. Credit cards are not only very easy to use, but they are also readily available. On account of the fact that it is so widely used, there is a substantial amount of concern regarding the protection of sensitive data from fraudulent activities and access by unauthorised individuals. For the purpose of preserving the trust and confidence of users, it is of the utmost importance to make certain that proper security measures are in place. Quantum machine learning (QML) is gaining popularity for classification applications, and a considerable number of the suggestions that have been made for it involve the utilisation of many qubits. This type of learning is becoming increasingly common. It is essential to make every effort to optimise the efficiency and effectiveness of each qubit before adding additional qubits. This should be done before adding more qubits. This is due to the fact that it is probable that these circuits will not always be able to function effectively in the generation of noisy intermediate-scale quantum (NISQ) systems. When compared to individual classifiers, traditional machine learning approaches, and the model that was recommended, it was discovered that the proposed model was more effective in reducing the obstacles connected with detecting credit card fraud. This concluded that the proposed model was more effective. When compared to earlier models, the model that was suggested has a greater degree of performance in terms of accuracy, precision, recall, and F1-score performance characteristics. This is the case when those parameters are measured. The findings that have been provided here provide a foundation for the creation of fraud detection algorithms that are more resilient and flexible. This is something that will become increasingly required as the number of methods that credit card fraud is committed continues to expand.

Keywords – Modified Shuffle Frog Leaping Algorithm, Quantum Machine Learning, Single-Qubit-Based Deep Quantum Neural Network, Credit Cards Fraud Detection, Convolutional Neural Network.

I. INTRODUCTION

The rise of online credit card fraud is biggest problems with contemporary online shopping. Payments made with both physically present and virtual cards are a source of public anxiety. Online payments (CNP) remain a major concern, even though banks' introduction of chip smart cards has greatly reduced CP fraud [1]. To reduce financial losses for consumers, modern encryptions and cutting-edge multi-factor authentication (MFA) methods like biometric technology have been created to thwart fraudulent activities, protect the credibility of card issuers and retailers, and so on [2]. However, con artists will always find a loophole to take advantage of. The proliferation of credit card transactions can be attributed to the enhanced ease and lightning-fast development of electronic services [3]. As a result, security threats like credit card theft have grown in frequency, worrisome for banks and their clients alike [4]. The estimated losses due to credit card fraud in 2019, 2020, and 2021 were at $28.55, $28.50, and $32.34 billion, respectively, as reported by Nielsen [5]. Also, from $9.84 billion in 2011 to $32.34 billion in 2021, the world's losses from credit card theft have increased thrice [6]. Credit card fraud detection (CCFD) has seen extensive application of machine learning (ML) techniques, with state-of-the-art results achieved [7]. Each machine learning algorithm falls into one of four categories: supervised, unsupervised, semi-supervised, or reinforcement learning. The supervised learning (SL) approach is the most used machine learning technique for noticing credit card fraud [8]. In supervised learning, a labelled dataset is used to train ML algorithms. One example of a label is "not fraud" which indicates that the data point does not belong to the "fraud" category. SL methods typically figure out what the connection is between the input features and the labels that come out of the process [9].

Multiple investigations have shown that neural networks can detect fraudulent transactions in intricate credit card databases [10]. Neural networks, a subfield of machine learning, can learn either with human-like guidance or independently, drawing inspiration from the way the brain works [11]. Complex patterns can be better analysed and predictions made by using multi-layer neural networks, often known as deep learning (DL). It is possible to detect using DL approaches. The most popular DL-based networks for credit card transaction modelling and analysis are recurrent neural networks (RNN) and variations like long short-term memory (LSTM) and generalised recurrent units (GRU) [12]. Some of the methods used to detect credit card fraud include Deep Learning, Machine Learning, and Statistical Analysis. When looking for unusual activity in credit card transactions, statisticians use tools including clustering, hypothesis testing, and regression [13]. Machine learning, on the other hand, analyses past data using algorithms to identify fraudulent actions as they happen [14]. The use of neural networks in deep learning approaches allows for the autonomous identification of detailed patterns and features in large datasets, leading to very effective fraud detection. Despite the abundance of cyber fraud detection methods, no system successful in delivering both efficiency and accuracy at a high level [15]. As a result, in order to launch cyber fraud detection innovation projects, academics and the banking sector need a synopsis of current practices and a critical evaluation of relevant recent research.

While current computer power constraints are limiting machine learning, scientists are investigating the possibility of merging quantum computing with machine learning in order to process classical data using ML algorithms [16]. Quantum Machine Learning (QML) is an emerging field of study that combines classical machine learning principles with those of quantum computing. Consequently, the goal of QML is to develop quantum apps for various ML algorithms, leveraging both the scalability and learning capabilities of ML algorithms and the processing power of quantum computers [17].

Our new single-qubit quantum CNNs are introduced to the study along with multiple implementation strategies for bringing the single-qubit technique to quantum CNNs. In particular, 1) to develop a technique that preserves data spatial relationships by means of parametrised convolutional filters, and 2) to modify this technique to handle data as it is, without resorting to expensive flattening preprocessing. Then, by uploading data based on a single qubit, to can simply create the quantum CNNs. In order to advance the accuracy of the classification, MSFLA extracts the relevant aspects. In order to prove that the suggested model is computationally efficient, to must test its ability to efficiently integrate varied base models, manage complicated algorithms, and implement elaborate feature engineering.

Here is the breakdown of the remaining sections of the paper: Section 2 lists pertinent literature; Section 3 stretches a high-level overview of the suggested classical; Section 4 details the analysis of the results; and Section 5 draws a conclusion.

II. RELATED WORKS

By identifying relevant aspects, Sorour et al., [18] improve the aptitude to correctly recognise financial CCF transactions. Their methodology is based on the Brown-Bear Optimisation (BBO) algorithm. When it comes to improving classification accuracy and reducing dimensionality, BBO has you covered. It is cloned into a binary variation called Binary BBOA (BBBOA) after being modified by randomly altering the positions to increase exploration and exploitation capabilities. The projected approach makes use of ML classifiers such as Xgb-tree, Support Vector Machine (SVM). This approach is tested on the Australian credit dataset alongside the standard BBOA and ten existing optimisers, including: Binary African Vultures Optimisation (BAVO), Binary Salp Swarm Algorithm (BSSA), Binary Atom Search Optimisation Binary Grasshopper Optimisation Algorithm (BGOA), and Binary Sailfish Optimiser (BSFO). With a classification accuracy of up to 91% and an attribute reduction length down to 67% in the utilised dataset, the proposed procedure clearly outperformed the alternatives using Wilcoxon's rank-sum test. Using ten benchmark datasets, to further test the proposed methodology and find that it outperforms the competition in the most used datasets across a variety of performance metrics. Finally, ten benchmark datasets taken from the UCI source are used to further validate the projected methodology. In majority of the datasets that were used, it fared better than its competitors on several performance criteria.

Khalid et al. [19] presented a original ensemble classical that integrates boosting classifiers, random forests, k-nearest neighbors, supporting vector machines, and bagging. The widespread issue of dataset imbalance in credit card datasets can be overcome by utilizing this ensemble model, which combines under-sampling with the Synthetic Over-sampling

Technique (SMOTE) on a few machine learning methods. The model is evaluated in a practical context using a dataset that contains records of Europeans' credit card transactions. The approach of the projected model includes data pre-processing, feature engineering, model selection, and assessment. Training and testing the model are made efficient using Google Colab's computational capabilities. Reducing challenges connected to credit card fraud detection was achieved more effectively by the model than by standard machine learning techniques, individual classifiers, or both. When comparing outperforms the current models. According to this study, ensemble techniques are an effective tool for combating fraudulent transactions. Building more robust and adaptable fraud detection systems is crucial in light of the ever-growing sophistication of credit card fraud techniques; the presented findings lay the groundwork for this endeavor.

In order to better notice credit card fraud, Baria et al., [20] suggests combining deep learning with linear regression models. To make sure the decision-making process is simple and easy to understand, the suggested method uses deep learning to capture complicated, non-linear correlations and high-dimensional designs in transaction data, and then uses linear regression to make sure everything is easy to understand. To begin, our hybrid model uses a deep learning architecture to glean useful features from unprocessed transaction data. More especially, it recurrent neural network (RNN). A linear regression model is used to classify the features in the end. Financial organisations may improve their performance and better understand what characteristics lead to fraudulent transactions by combining deep learning with linear regression. This helps them fight credit card fraud, which is an ongoing problem.

Zhu et al., [21] suggests a novel approach to detecting performance improvement by merging Neural Networks (NN) with Synthetic sampling Procedure). Focussing on technological advances for strong and accurate fraud detection, the study tackles the inherent imbalance in data. According to the results, when compared to standard models, the combination of NN and SMOTE performs better. This proposes that it could be a good option for credit card fraud detection scenarios where the dataset is imbalanced. In order to avert fraudulent financial transactions, this study adds to the continuing attempts to find better and more efficient ways to do it.

For credit card fraud finding, Bao et al. [22] suggests a BERT model to deal with imbalanced and high-dimensional datasets. The model improves the accuracy of fraud finding by utilising BERT's pre-training to identify semantic resemblance. The suggested method accomplishes an impressive 99.95% accuracy in identifying fraudulent transactions by means of thorough data preprocessing and model training. The research highlights the significance of using cutting-edge deep learning methods such as BERT to counteract developing fraud strategies in the online banking sector.

Innovative usage of the most recent Transformer models for stronger and more accurate fraud detection have been the attention of Yu et al., [23]. Thoroughly processing the data sources and balancing the dataset to solve data sparsity significantly, to ensured the data's dependability. To ensure the new Transformer model's reliability and practicality, to compared its performance with several widely used models, Precision, and Recall to compare these models thoroughly. These in-depth comparisons and analyses allow us to offer the readers a robust anti-fraud system that shows great promise. According to the findings, the Transformer model is a huge step forward in the industry and not only works well in the usual suspects, but it also has promising future uses in less common domains, such as fraud detection.

III. PROPOSED METHODOLOGY

In this section, the brief explanation of projected methodology for credit card detection is graphically publicized in **Fig 1**.

In the beginning of this process, there is the dataset, which is made up of transactions, some of which might be indicative of fraudulent behaviour. This stage involves cleaning the data by completing tasks such as eliminating null values and normalising the data in order to get the data suitable for feature selection and classification. This stage is necessary in order to get the data ready for these processes. In order to choose features, the Modified Shuffled Frog Leaping Algorithm (MSFLA) is utilised. This algorithm is responsible for the selection process. This stage helps in picking the characteristics from the dataset that are currently the most relevant, which in turn improves the accuracy and efficiency of the classification model. Additionally, this stage helps in selecting the characteristics that are the most relevant. In order to accomplish the task of classification, the selected characteristics are fed into a machine learning model that is founded on quantum mechanics. This model's objective is to classify transactions as either legal or fraudulent, depending on the circumstances. Following the classification phase, validation analysis is carried out in order to verify the effectiveness of the model and ensure that it accurately differentiates between genuine and fraudulent transactions. This takes place after the classification process has been completed. Last but not least, the system separates the transactions into two unique groups, which are as follows: Examples of Transactions That Are Common Deceptive financial dealings and transactions.

It was from kaggle.com that the dataset was obtained [24]. It included purchases made in January 2024 using American credit cards. Over the progression of two days, a entire of 284,807 recorded, with 491 of those identified as fraudulent. To guarantee client confidentiality and account for the dataset's extreme imbalance—fraudulent transactions accounted for almost 0.172% of altogether transactions—some attributes were translated into Principal Component Analysis (PCA). **Table 1** shows that other properties like class, amount, and time are untouched, while features labelled as $V1, V2, V3, and\ V21$ represent the variables that were transformed using PCA.

Data Preprocessing

In order to fine-tune the data selection, the dataset went through multiple stages. Specific approaches were used to filter out less useful features due to the relatively small trial size (995 declarations) and the presence of a significant number of characteristics (887). To begin, to discarded data sets that had more than half of their values missing because to couldn't draw any conclusions from them. In addition, to removed features with comparable values since they weren't adding to the data's variability. In addition, the analysis did not include text qualities or categorical variables that had more than 30 categories.

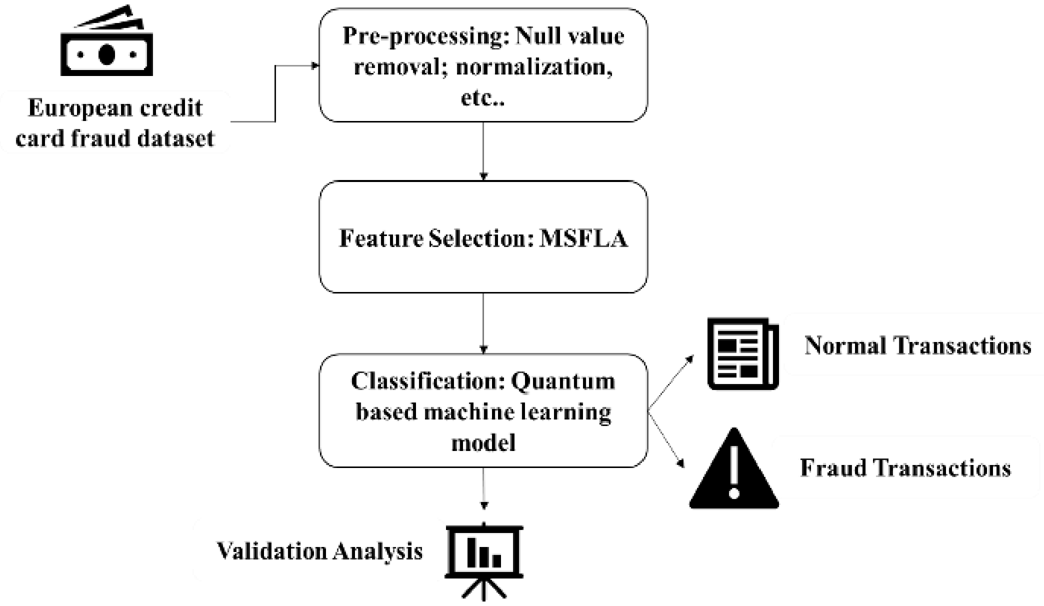

Fig 1. Workflow of the Projected Classical.

Dataset collection

Table 1. Dataset Description

Descriptions	Characteristics
Transaction amount	Class
Time in seconds to designate the timeline used among the present transaction besides the previous one.	Time
1-fraud 0-not fraud	Amount
Refers to the limit of the credit card	LIMIT_BAL

Feature Selection using MSFLA

In enhance the classification accuracy, the MSFLA [25] is employed to choose the best features from the pre-processing model. Each possible answer in SFLA is represented by a digital frog's position, and a collection of these frogs stands for the population of answers. Subsequent the generation of the initial populace P, the following procedures are repeated endlessly or until a limiting disorder is reached.

$$x_w' = x_w + rand \times (x_b - x_w) \tag{1}$$

$$x_w' = x_w + rand \times \left(x_g - x_w\right) \tag{2}$$

where rand is an arbitrary value that follows [0.1].

A new populace P is built by rearranging the sequence of all the developed memeplexes. The idea of differentiated search within memeplexes is rarely measured, and the search technique and criteria used to construct memeplexes are typically the same, as indicated before. Adding new search operators and parameters improves search efficiency by making it easier to avoid local optima and strengthening search capacity. This study introduces MSFLA as a method for extracting useful attributes from unstructured data. Phase two of MSFLA includes the varied search.

Initialization, Populace Separation, and the First Phase

In this study, a key of the difficult is considered as $\left[M_{\theta_1}, M_{\theta_2}, \dots, M_{\theta_n}\right]$ and a string $[q_1, q_2, \cdots, q_n]$, where M_{θ_j} is the owed for job $J_j, j = 1, 2, \cdots, n$, and q_l is agrees to J_l. These two strings have distinct purposes. A description of the decoding process follows. The machine Mk is used to select the machine for each work, and then all jobs are run simultaneously. $J_i, J_{i+1}, \cdots, J_j$ allocated on M_k—that is, $M_{\theta_i} = M_{\theta_{i+1}}, \cdots, = M_{\theta_j} = M_k$. The dispensation order of $q_l, l \in [i, j], i < j$, and M_k sequentially.

This is the next step after randomly creating the initial population P: dividing the population. Pick out the greatest s answers from set P and rank them from most effective to least. The next step is to provide the memeplexes with a subset of the initial response. Our initial response will be M_1, followed by M_2 assign alternative solutions to memeplexes. In this method, two solutions are picked at random and equated to determine which one is better. Next, to add x_i (x_j) to M_1. Pick one key at random and add it to M_1 if there are more than one key with the same purpose. Returns the options that were not picked to the population P. The identical method for finding an answer for $\mathcal{M}_2, \mathcal{M}_3, \dots, \mathcal{M}_s$ and keys are owed. Obviously, $N = s \times \theta$, where θ symbolizes memeplex.

Because it is so much better at exploring, global search is only used at the beginning. Stage two involves the use of differentiated search algorithms that are based on evaluations of memeplex quality.

The Second Phase

Evaluation of hardly measured in SFLA. Memeplexes are evaluated based on their problem-solving capabilities and their ability to evolve. Deliberately Memeplex $\mathcal{M}_l$, its quality M_{eql} is defined by

$$M_{\text{eql}} = a_1 \times \frac{msq_{max} - msq_1}{msq_{max} - msq_{min}} + a_2 \times \frac{mvq_1 - mvq_{min}}{mvq_{max} - mvq_{min}} \tag{3}$$

where a_1, a_2 are real number, msq_1 and mvq_1 indicate solution quality of $\mathcal{M}_l$, respectively, $msq_{max} = \max_{l = 1,2,\cdots,s} \{msq_l\}, msq_{min} = \min_{l = 1,2,\cdots,s} \{msq_l\}$, mvq_{max} and $mvq_{\min}$ represent all memeplexes, distinctly.

After entirely solutions in $\mathcal{M}_l$ are prearranged, let H_1 indicate primary $\theta/2$ keys except x_b and H_2 is the set of the endured $\theta/2$ keys in $\mathcal{M}_l$,

$$msq_l = C_{max}(x_b) + \beta_1 \times \bar{C}_{max}(H_1) + \beta_2 \times \bar{C}_{max}(H_2) \tag{4}$$

where $\bar{C}_{max}(H_i)$ is the regular makespan of all keys in H_i, i = 1, 2, $\beta_i . i = 1, 2$ is a real number. Solutions of H_1 are those of H_2; thus, to set $\beta_1 > \beta_2$ to reflect this feature. $\beta_1 = 0.4$ and $\beta_2 = 0.1$ are gotten by trials.

Let Im_x designate the better sum of x group. When $x \in M_l$ is designated x_w, in general SFLA, if than x, then $Im_x = Im_x + 1$. Se_x is the total primary generation.

$$mvq_1 = \sum_{x \in M_l} Im_x / \sum_{x \in M_l} Se_x \tag{5}$$

For solution x_i, its act_{x_i} is used to assess is figured by

$$act_{x_i} = Im_{x_i} / Se_{x_i} \tag{6}$$

The second stage is unprotected as shadows.

(1) Perform separation, estimate Meq_l for completely in descending order of Meq_l, and construct set $\Theta = \{M_l | meq_l > \overline{Meq}, l \leq \eta \times \theta\}$.
(2) For correspondingly memeplex $M_l, M_l \notin \Theta$, reappearance the successive steps R_1 aeras if $|\tau| > 0$, execute global search special y 2 T ; else accomplish among x_b and a key $y \mid \in M_l$ with $act_y \geq act_x$ for all $x \in M_l$.
(3) For each memeplex $M_l \in \Theta$,
    1. sort all keys in M_l in the suppose $C_{max}(x_1) \leq C_{max}(x_2) \leq \cdots \leq C_{max}(x_\theta)$, and hypothesis a set $\varphi = \{x_i | dist_{x_i} < \overline{dist}, i \leq \theta/2\}$.
    2. Recurrence the subsequent ladders R_2 times, key $x_i \in M_l/\varphi$ if $act_{x_i} > 0.5$, then select a key $y \in \varphi$ by on Pr_y, execute among x_i and y, and inform memory T ; else among x_i and a result z with $act_z \geq act_{x_i}$ for all $x_i \in M_l$ and T .
(4) Execute hunts on each key $x \in \varphi$.
(5) Perform novel populace shuffling.

where $dist_{x_i} = |C_{max}(x_i) - C_{max}(x_b)|$ is distinct for each key $x_i \in M_l$ and $\overline{dist}$ is the regular value of all $dist_{x_i}$ in M_l. η is a real sum besides set to be 0.4 by trials, $\overline{Meq}$ designates the average excellence, Θ is the Pr_y is a likelihood besides different by

$$Pr_y = \frac{|\varphi| - rank_y}{|\varphi|} \times \frac{Im_y}{\sum_{x \in \varphi} Im_x} \tag{7}$$

where $rank_y$ ranks clearly and is a numerical value, which brings us to the first stage of step three of the aforementioned process.

In the second phase, after all in all in the Meql, suppose $Meq_1 \geq Meq_2 \geq \cdots Meq_s$.

Memory T is used keys. The maximum degree $|T|_{\max}$ is given payment. to set $|T|_{\max}$ to be 200 by trials. When keys exceeds $|T|_{\max}$, a key x can be one.

Six used. N_1 is exposed below. Arbitrarily the machine M_k with the largest C_{max}^k and machine M_g with the smallest $C_{\max}^g$, where $C_{\max}^k$ and $C_{\max}^g$ are last treated job on M_k besides M_g, individually. N_2 is achieved in the subsequent way. Decide on a machine M_k with the major $C_{\max}^k$ besides a job J_i with the major processing time p_{ki} on M_k, arbitrarily pick a machine M_g, g≠k and a job J_j with the largest p_{gj} and conversation J_i and J_j among M_k and Mg.

N_3 is described as shadows. Arbitrarily choice machines M_k besides M_g and talk a job J_i with the chief p_{ki} besides a job J_j with the major pgj among machines. N_1, N_2, N_3 only act on the string.

N_4, N_5, N_6 are string operations that involve exchanging two genes, inserting one gene into a randomly chosen new site, and inverting the genes between two spots. $k_1, k_2, k_1 < k_2$.

Multiple key x, let $u = 1$, reappearance the succeeding ladders V periods: yield a key $z \in N_u(x)$, u=u+1, let $u = 1$ if $u = 7$, and $Im_x = Im_x + 1$.

The second part of the worldwide search follows the same protocol as the first.

The present SFLA [25] constructs a new P-population using the s-developed memeplexes. The following methods of population reshuffling are employed in this study: Incorporating the top memeplexes from both besides new (P) populations into the latter is the goal of this process. By means of scientific experiments,

To establish $\gamma = 0.1 \times |T|_{max}$.

Put another way, you can improve P's less than ideal results by using memeplex search or shuffling. The first phase involves applying act_x to an optimisation object x global search; the second phase focusses on finding a good memeplex by performing a manifold search on the keys in. A global search is all that's done for other memeplexes; on top of that, a number of parameters, $R_1, R_2, R_1 \neq R_2$, used, besides, as a importance, distinguished search is applied.

Classification using Quantum Computing Machine Learning

This study employs machine learning based on quantum computing to categorise credit card fraud detection. Similar to traditional networks, single-qubit encoding allows for the efficient generation of a very complicated feature space by means of several upload layers of input data. One potential drawback is that it only supports one-level encoding, which can be problematic for data categorisation and other activities that rely on spatial information of data. One essential part of deep learning convolutional layers is the incorporation of local data areas. The usual method involves using a filter, also called a "sliding window," to collect data from a square region of size F × F. A value for that data region would be obtained in conventional ML by applying a kernel operation.

Taking a similar tack is the starting point for our suggested change. The data's original shape is preserved instead of being flattened into a column vector step. The data is thus put through a filter with dimensions F × F, dividing it into a separate grid of F × F squares. Afterwards, the aforementioned single-qubit encoding strategy is used to encode each square region of data qubit row by row, with values (x_i) and appropriate filter weights (θ_i, φ_i) as parameters.

It is possible to encode data in a way that preserves the spatial relationships between its components by using this method. In order to make things clear, instead of giving a set of trainable strictures to every square $F \times F$ data region, the filter is given a set of six weight parameters that match θ and φ in equation (8). This ensures that the six parameters are applied to all three-data sets produced by the filter in the same way. This technique narrows the filter parameter set down to a manageable six.

To seek to show that good results can be obtained with the fewest parameters, even if it is recognised that each F × F region could have numerous unique sets of six parameters. In light of this, the experiments presented here will all make use of a single filter with a total of six parameters. Nevertheless, there are benefits and drawbacks to each of the two setups mentioned, and they provide slightly different approaches to data classification. Reason for its inclusion in this section: it may lead to the exploration of many avenues in future study.

Classification Pipeline and Loss Calculation

The input-output flow from classification has not been made clear, while the recommended encoding approach has been stated. The overall goal of this fidelity-based measurement approach is to minimise the fidelity among a encodings and their corresponding target states. This is how it is accomplished. Every piece of data with a class value of 0 or 1 is given a target state of 0 or 1 in a binary classification task, where the data set has a size of D. As long as the target states are as far apart as possible, this method can incorporate any number of classes.

This is the starting point for encoding the pixel values onto the qubit using the suggested method. The next step is measurement, which involves extracting the qubit's fidelity against each target class state individually. To summarise, fidelity F is a sum between zero and one that quantum states are comparable. Two quantum states are more comparable in direction when their fidelity is high. Classification is then thought to have been successful if the highest-class fidelity value provided was used. After that, the loss function that follows is derived from the one that was previously used.

:

$$\frac{1}{2D}\sum_{m=1}^{D}\sum_{c=1}^{C}((F(x_d, \theta, \varphi)_c - F_c)^2) \tag{8}$$

where D is data used, C is the amount of classes, $F(x_d, \theta, \varphi)_c$ is the slow datapoint d with admiration to class c, and F_c is the expected measured. In order to understand, a datapoint belonging to class 0 has a target public of |0|, while class 1 has an expected fidelity value of 0 and class 0 has an expected fidelity value of 1. One would get a fidelity measurement of one if the qubit were in state |0|. At fidelity level 0, the qubit would be in state |1|. For example, let's pretend the qubit was $|\psi >= (|0 > +|1 >)/((2)^{1/2})$, then the loyalty measurement is given by

$$F(x_d, \theta, \varphi)_c = |\langle \psi_c | \psi(x_d, \theta, \varphi) \rangle|^2 \tag{9}$$

Here, $F(x_d, \theta, \varphi)_c$ = 0.5 for c = 0. Expected faithfulness values can using (4) by cycling through value with one additional.

A entire representation of the categorisation to output, can be seen in an algorithm. To summarise, square sections of data are extracted one at a time using filters that are run over each data set. Then, with the input values region and the filter weights as parameters, unitary operations are executed on the qubit one after the other. At the end of the encoding process, to check for consistency with the class states by measuring fidelity.

The purpose of assigning a placeholder value of 0 to x if it is not divisible by 3 is to make the hardcoded variables β, γ, and δ clear; this value has no extra impact on the rotation of the qubits. Unitary operations are applied sequentially, with each value ϋ, γ, and δ being delivered in turn, by cycling i in multiples of 3.

IV. RESULTS AND DISCUSSION

This study makes use of a wide variety of computer specifications and tools in its development and validation of the proposed system. To develop and assess the proposed scheme and conduct experiments with numerous machine learning algorithms, to have employed Python running on a 64-bit Microsoft Windows 10 operating scheme at the software level. To train and validate each model, to utilised 10-fold cross-validation. In terms of hardware, to ran our model implementations and evaluations on a high-performance computing platform outfitted with an $Intel\ ®Xeon®\ CPU\ E3-1241\ v3\ @3.5GHz,$ 16 GB of RAM, and a 4 GB GPU. So, to have used pertinent features gained from mathematical set theory to assess model. **Table 2** displays the results of the experimental evaluation of the suggested model using current methods and Various indicators are graphically analysed in **Fig 2**

To evaluate the suggested model against CNN, Deep Belief Network (DBN), Extreme Learning Machine (ELM), LSTM, RNN, and accuracy, recall, and precision. Both the classification accuracy and the resilience of each model are assessed. The ELM achieved an F1-score of 90.22% and an accuracy of 90.55%. With a balance between recall (90.55%) and precision (90.75%), this model shows ongoing performance despite being one of the lowest in our sample. Unfortunately, due to its simplicity and quickness during training, ELM could overlook intricate data patterns, leading to subpar results. The F1-score increased to 93.13% and the DBN accuracy to 94.85%. It can generalise with a good mix of sensitivity and precision, as seen by its high recall (94.09%) and precision (93.17%). LSTM and CNN outperformed DBN.

Table 2. Comparative Study of Projected with Existing Techniques

Models	**Accuracy**	**F1**	**Recall**	**Precision**
ELM	90.55	90.22	90.55	90.75
DBN	94.85	93.13	93.09	93.17
LSTM	95.84	95.78	94.76	96.86
RNN	95.97	95.07	94.07	95.08
CNN	95.78	95.93	95.71	96.16
Proposed model	97.06	96.94	96.67	97.23

Accuracy, F1-score, and precision were all 95.84 percent for the LSTM model. Although LSTM is accurate, it fails to recognise good samples due to its lower recall of 94.76%. Performance is enhanced as a result of proper capturing of data temporal dependencies. While both RNN and LSTM achieve an accuracy of 95.07%, RNN's F1-score is lower at 95.07%. A small sensitivity trade-off is shown by the lowest recall (94.07%) among top-performing models. The competitiveness of RNN precision (95.08%) is questioned by declining gradients during processing of long sequences, which could account for its slightly worse recall With an F1-score of 95.33% and an accuracy of 95.78%, the CNN model outperforms all others. CNN's 95.71% recall and 96.16% precision show that it can detect positives and avoid false positives. The strong F1-score achieved by CNN demonstrates its ability to classify, handle spatial data, and extract features in a balanced manner.

A remarkable 97.06% accuracy was achieved by the suggested model. With an F1-score of 96.44%, it shows that it performs on par with other models in terms of accuracy (97.23%) and recall (96.67%). Thanks to its high recall and accuracy, the proposed model can identify the vast majority of positive scenarios while simultaneously decreasing the number of false positives. Its improved accuracy in difficult classification tasks might be the result of a model design that combines spatial and temporal information extraction techniques. The suggested model is the most trustworthy option because it outperforms conventional wisdom in terms of accuracy and precision. The results demonstrate that the suggested design resolves model constraints and enhances classification.

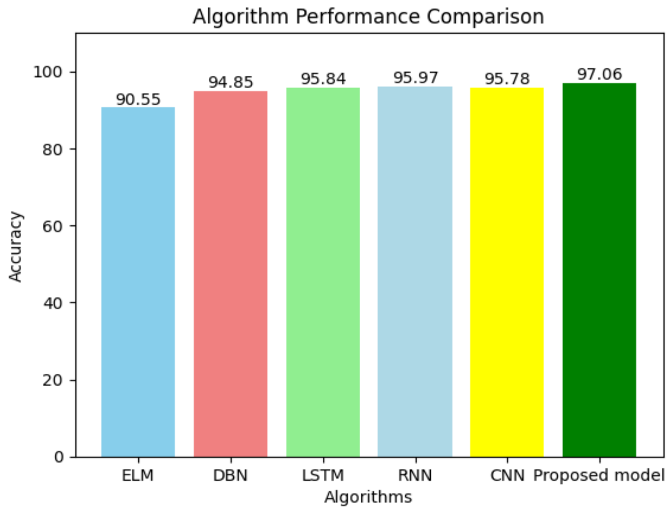

Fig 2. Visual Representation of Accuracy.

Comparative analysis of the proposed model against existing techniques, evaluating performance metrics. The proposed model excels with the uppermost accuracy of 97.06%, an F1-score of 96.94, as recall of 96.67, besides precision of 97.23%, demonstrating superior performance over other models. LSTM follows closely with 95.84% accuracy, 95.78 F1-score, 94.76 recall, and 96.86 precision, while RNN achieves 95.97% accuracy, 95.07 F1-score, 94.07 recall, and 95.08 precision. CNN shows competitive results with 95.78% accuracy, 95.93 F1-score, 95.71 recall, besides 96.16 precision. DBN and ELM exhibit lower performance, with DBN achieving 94.85% accuracy and ELM trailing at 90.55%. Overall, the projected model outdoes all other techniques. **Fig 3** shows visual representation of F1-Score.

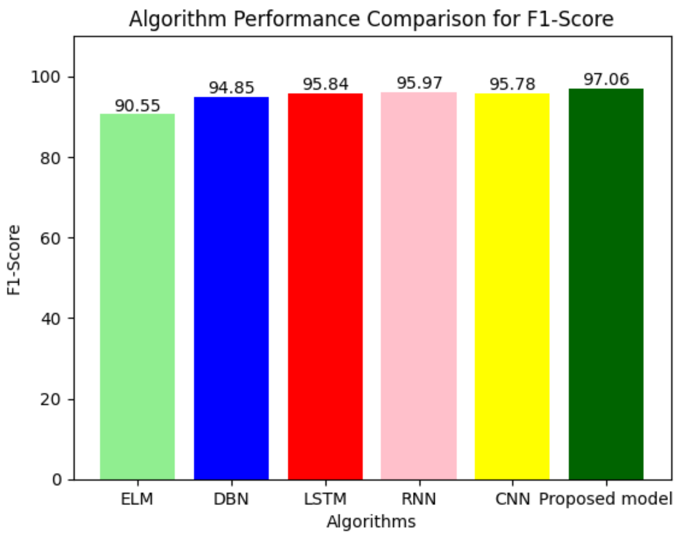

Fig 3. Visual Representation of F1-Score.

In terms of Accuracy, F1-score, Recall, and Precision, your bar chart compares the proposed model to ELM, DBN, LSTM, RNN, and CNN. The chart's most salient points are as follows: In terms of accuracy, the proposed model ranks first with a score of around 97%, while the RNN and LSTM models come in second and third, respectively, with scores of 95%. Similar to LSTM, CNN performs exceptionally well in this metric. The accuracy of ELM is around 90%, which is the lowest. The F1 score is: The suggested model outperforms CNN with an F1-score of around 96%. The 95% confidence level is where LSTM and RNN meet. The F1-scores of both DBN and ELM are lower; ELM's is around 90% and DBN's is 93%. The recommended model came in second, while CNN had the best recall. While CNN and the proposed model both have higher recall, LSTM and RNN are still quite good at what they do. At the bottom of the recall scale are both DBN and ELM. To be more specific: the proposed model shows a high degree of accuracy, around 97%, and a remarkable capacity to remove false positives. Following LSTM and RNN with scores of 95-96% is CNN. Although DBN is marginally better than ELM, both have a lesser degree of accuracy. Because it outperformed all four criteria, the proposed model is the best fit for this study. Two of CNN's strong points are recall and F1-score. The accuracy and recall of LSTM and RNN are higher than those of DBN and ELM. The visualisation provides support for the idea that the suggested model has better categorisation capabilities. **Fig 4** shows visual representation of Recall and Precision.

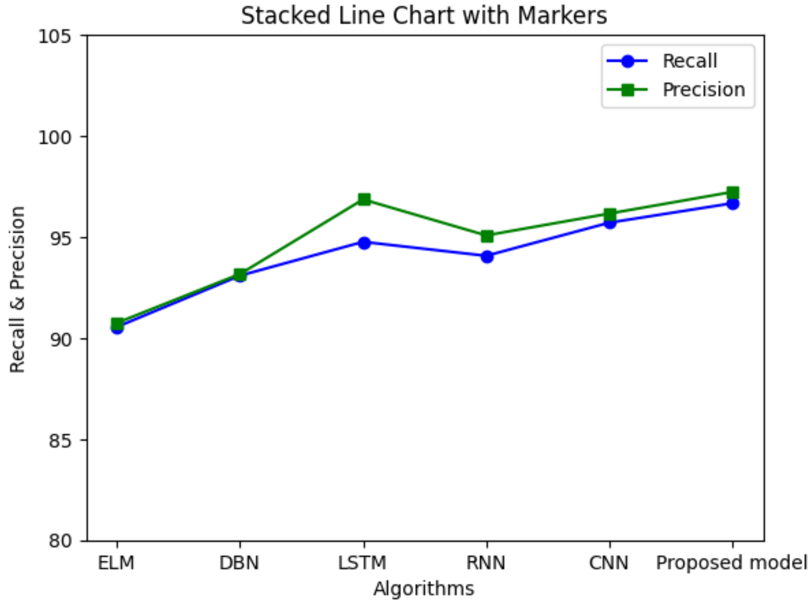

Fig 4. Visual Representation of Recall & Precision.

V. CONCLUSION

The paper shed light on the gravity of the widespread issue of credit card fraud by doing in-depth research on the relevant literature and bringing it to light. A huge number of people have been killed as a direct result of the growth in identity theft, particularly completed credit card fraud. As a consequence of this, these individuals have suffered both financial losses and emotional anguish as a consequence of their deaths. For the purpose of demonstrating a cutting-edge method for spotting fraudulent financial actions among employees in the workplace. The first thing that we do in our process is classify customers according to the transactions that they have completed. After that, we construct a profile cardholder for each customer based on the patterns of behaviour that they have demonstrated. The classification of fraud detection is accomplished through the utilisation of a framework for machine learning that is based on quantum computing within the context of this inquiry. For the purpose of improving the accuracy of classification, MSFLA is employed as a feature selection. We worked with a credit dataset from Europe and employed a number of various metrics, such as accuracy, precision, recall, and the F1-measure, in order to validate the reliability of the suggested model. This allowed us to determine whether or not the model was effective. Additionally, it is of the utmost importance to do research into data sampling methods that are capable of being updated in order to accommodate evolving data distributions throughout the course of time. The detection of fraudulent activity patterns on credit cards is heavily dependent on this study. This is due to the fact that fraudulent activity patterns may change over time, and in order for a model to be successful, it must be able to adapt to these changes. Furthermore, this study recommends undertaking additional research into approaches that can increase the capability of the recommended model to resist hostile assaults. Further research into these strategies is suggested in this work. The investigation of various tactics that have the potential to lessen the risk of hostile attacks that are directed at machine learning models would be of great use. Last but not least, research in the future will be able to evaluate how well the model takes into account the increasing number of datasets and the growing demand for processing power. Within the context of this method, the utilisation of distributed computing or parallel processing could be utilised in order to guarantee efficient processing even when the size of the dataset is increased.

CRediT Author Statement

The authors confirm contribution to the paper as follows:

Conceptualization: Deepa N, Jayaraj R, Suguna M, Sireesha Nanduri, Banda SNV Ramana Murthy, Jebakumar Immanuel D; **Methodology:** Deepa N, Jayaraj R and Suguna M; **Writing- Original Draft Preparation:** Jayaraj R, Suguna M and Sireesha Nanduri; **Supervision:** Deepa N, Jayaraj R and Suguna M; **Validation:** Jayaraj R, Suguna M and Sireesha Nanduri; **Writing- Reviewing and Editing:** Jayaraj R, Suguna M and Sireesha Nanduri; All authors reviewed the results and approved the final version of the manuscript.

Data Availability
No data was used to support this study.

Conflicts of Interests
The author(s) declare(s) that they have no conflicts of interest.

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References
[1]. A. Cherif, A. Badhib, H. Ammar, S. Alshehri, M. Kalkatawi, and A. Imine, "Credit card fraud detection in the era of disruptive technologies: A systematic review," Journal of King Saud University - Computer and Information Sciences, vol. 35, no. 1, pp. 145–174, Jan. 2023, doi: 10.1016/j.jksuci.2022.11.008.
[2]. Z. Salekshahrezaee, J. L. Leevy, and T. M. Khoshgoftaar, "The effect of feature extraction and data sampling on credit card fraud detection," Journal of Big Data, vol. 10, no. 1, Jan. 2023, doi: 10.1186/s40537-023-00684-w.
[3]. K. Patel, "Credit Card Analytics: A Review of Fraud Detection and Risk Assessment Techniques," International Journal of Computer Trends and Technology, vol. 71, no. 10, pp. 69–79, Oct. 2023, doi: 10.14445/22312803/ijctt-v71i10p109.
[4]. A. Mniai, M. Tarik, and K. Jebari, "A Novel Framework for Credit Card Fraud Detection," IEEE Access, vol. 11, pp. 112776–112786, 2023, doi: 10.1109/access.2023.3323842.
[5]. R. Van Belle, B. Baesens, and J. De Weerdt, "CATCHM: A novel network-based credit card fraud detection method using node representation learning," Decision Support Systems, vol. 164, p. 113866, Jan. 2023, doi: 10.1016/j.dss.2022.113866.
[6]. I. D. Mienye and Y. Sun, "A Deep Learning Ensemble With Data Resampling for Credit Card Fraud Detection," IEEE Access, vol. 11, pp. 30628–30638, 2023, doi: 10.1109/access.2023.3262020.
[7]. H. Fanai and H. Abbasimehr, "A novel combined approach based on deep Autoencoder and deep classifiers for credit card fraud detection," Expert Systems with Applications, vol. 217, p. 119562, May 2023, doi: 10.1016/j.eswa.2023.119562.
[8]. S. Stephe, V. Revathi, B. Gunapriya, and A. Thirumalraj, "Blockchain-Based Private AI Model with RPOA Based Sampling Method for Credit Card Fraud Detection," Sustainable Development Using Private AI, pp. 261–277, Jul. 2024, doi: 10.1201/9781032716749-14.
[9]. M. Habibpour et al., "Uncertainty-aware credit card fraud detection using deep learning," Engineering Applications of Artificial Intelligence, vol. 123, p. 106248, Aug. 2023, doi: 10.1016/j.engappai.2023.106248.
[10]. S. Bakhtiari, Z. Nasiri, and J. Vahidi, "Credit card fraud detection using ensemble data mining methods," Multimedia Tools and Applications, vol. 82, no. 19, pp. 29057–29075, Mar. 2023, doi: 10.1007/s11042-023-14698-2.
[11]. L. Ni, J. Li, H. Xu, X. Wang, and J. Zhang, "Fraud Feature Boosting Mechanism and Spiral Oversampling Balancing Technique for Credit Card Fraud Detection," IEEE Transactions on Computational Social Systems, vol. 11, no. 2, pp. 1615–1630, Apr. 2024, doi: 10.1109/tcss.2023.3242149.
[12]. E. Strelcenia and S. Prakoonwit, "Improving Classification Performance in Credit Card Fraud Detection by Using New Data Augmentation," AI, vol. 4, no. 1, pp. 172–198, Jan. 2023, doi: 10.3390/ai4010008.
[13]. H. Ahmad, B. Kasasbeh, B. Aldabaybah, and E. Rawashdeh, "Class balancing framework for credit card fraud detection based on clustering and similarity-based selection (SBS)," International Journal of Information Technology, vol. 15, no. 1, pp. 325–333, Jun. 2022, doi: 10.1007/s41870-022-00987-w.
[14]. S. Xiang et al., "Semi-supervised Credit Card Fraud Detection via Attribute-Driven Graph Representation," Proceedings of the AAAI Conference on Artificial Intelligence, vol. 37, no. 12, pp. 14557–14565, Jun. 2023, doi: 10.1609/aaai.v37i12.26702.
[15]. P. Gupta, A. Varshney, M. R. Khan, R. Ahmed, M. Shuaib, and S. Alam, "Unbalanced Credit Card Fraud Detection Data: A Machine Learning-Oriented Comparative Study of Balancing Techniques," Procedia Computer Science, vol. 218, pp. 2575–2584, 2023, doi: 10.1016/j.procs.2023.01.231.
[16]. J. Appadurai et al., "Prediction of EV Charging Behavior using BOA-based Deep Residual Attention Network," Revista Internacional de Métodos Numéricos para Cálculo y Diseño en Ingeniería, vol. 40, no. 1, 2024, doi: 10.23967/j.rimni.2024.02.002.
[17]. S. Jiang, R. Dong, J. Wang, and M. Xia, "Credit Card Fraud Detection Based on Unsupervised Attentional Anomaly Detection Network," Systems, vol. 11, no. 6, p. 305, Jun. 2023, doi: 10.3390/systems11060305.
[18]. S. E. Sorour, K. M. AlBarrak, A. A. Abohany, and A. A. A. El-Mageed, "Credit card fraud detection using the brown bear optimization algorithm," Alexandria Engineering Journal, vol. 104, pp. 171–192, Oct. 2024, doi: 10.1016/j.aej.2024.06.040.
[19]. A. R. Khalid, N. Owoh, O. Uthmani, M. Ashawa, J. Osamor, and J. Adejoh, "Enhancing Credit Card Fraud Detection: An Ensemble Machine Learning Approach," Big Data and Cognitive Computing, vol. 8, no. 1, p. 6, Jan. 2024, doi: 10.3390/bdcc8010006.
[20]. J. B. Baria, V. D. Baria, S. Y. Bhimla, R. Prajapati, M. Rathva and S. Patel, "Deep Learning based Improved Strategy for Credit Card Fraud Detection using Linear Regression," Journal of Electrical Systems, 20(10s), 1295-1301, 2024.
[21]. M. Zhu, Y. Zhang, Y. Gong, C. Xu and Y. Xiang, "Enhancing Credit Card Fraud Detection A Neural Network and SMOTE Integrated Approach," 2024, arXiv preprint arXiv:2405.00026.
[22]. Q. Bao, K. Wei, J. Xu and W. Jiang, "Application of Deep Learning in Financial Credit Card Fraud Detection," Journal of Economic Theory and Business Management, 1(2), 51-57, 2024.
[23]. C. Yu, Y. Xu, J. Cao, Y. Zhang, Y. Jin and M. Zhu, "Credit card fraud detection using advanced transformer model," 2024, arXiv preprint arXiv:2406.03733.
[24]. https://www.kaggle.com/mlg-ulb/creditcardfraud
[25]. Z. Zhao, M. Wang, Y. Liu, Y. Chen, K. He, and Z. Liu, "A modified shuffled frog leaping algorithm with inertia weight," Scientific Reports, vol. 14, no. 1, Feb. 2024, doi: 10.1038/s41598-024-51306-1.