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Optimizing Banking Operations with AI Using BiGRU-FOA for Financial Data Analysis

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Abstract: The financial sector is undergoing a profound transformation with the integration of artificial intelligence (AI) and cloud computing technologies. A notable advancement is the deployment of a deep learning classification system that integrates Bidirectional Gated Recurrent Units (BiGRU) with the Fruit Fly Optimization Algorithm (FOA) to enhance complex banking operations. The BiGRU model efficiently analyzes financial transactions, customer profiles, and risk patterns by processing sequential data with long-term dependencies. FOA, inspired by the foraging behavior of fruit flies, optimizes the network's performance and computational efficiency. A cloud-based implementation of the BiGRU-FOA framework ensures scalability, real-time processing, and seamless integration with existing banking infrastructure. Experimental results demonstrate that BiGRU-FOA outperforms traditional machine learning techniques and standalone deep learning models in financial dataset classification, achieving superior accuracy, precision, and recall. This model enhances fraud detection, customer segmentation, and credit risk assessment, paving the way for more efficient and intelligent banking operations. By leveraging this advanced AI-driven framework, banks can improve decision-making processes, enhance operational efficiency, and offer personalized financial services. This research highlights the potential of deep learning and optimization technologies in revolutionizing the banking sector, enabling a more secure, efficient, and customer-centric approach.

Keywords: AI-driven banking solutions; BiGRU-FOA Optimization; deep learning in banking; financial data classification; fraud detection

1 INTRODUCTION

The financial services industry experiences an ongoing fundamental change because of quick technology adoption. Financial institutions and investment firms together with banks adopt Artificial Intelligence (AI) and machine learning and data-driven approaches to tackle their current challenges. Advanced technologies boost operational efficiency and simultaneously help financial establishments deliver more precise decisions along with individualized customer service and protective risk management capabilities. The main characteristic of financial sectors rests in their ability to produce huge streams of daily operational data comprised of transactions along with profiles and trends and compliance records. Since data volumes are abundant they create difficulties for real-time analysis alongside interpretation. The financial sector depends on its capability to analyze and derive essential knowledge from vast data repositories for its market leadership advantage. Advanced computational techniques use AI domain capabilities to untangle complex and enormous datasets which resolve industry data processing challenges [1].

AI technology proves most valuable for detecting frauds while providing credit scores and conducting risk assessments and segmenting customers and creating financial predictions. The detection of fraud needs advanced systems which detect irregular patterns so companies can minimize losses and keep their customers trust intact. The assessment of future outcomes depends on historical data analysis in both credit scoring and risk assessment operations which leads to better lending and investment determination. Using advanced data analysis techniques proves essential for improving both security levels and operational efficiency in this environment. The financial sector today experiences a primary transformation trend through digital advancements which include cloud computing and big data analytics as well as AI-driven automation. The current transformation has improved both financial institution scalability and operational financial efficiency while providing better reaction capabilities for market requirements and regulatory standards. Through digital infrastructure organizations can generate innovation through its ability to process big data at large scale [2].

The core focus of this shift rests on obtaining real-time analytical capabilities and decision-making capacity. The financial markets function within a high-speed dynamic environment which produces substantial negative effects from delayed processing or decision-making. Finance systems connected with AI technology enable automated task execution alongside instant delivery of meaningful insights. The ability for real-time processing stands as a critical need to optimize high-frequency trading since quick decisions produce profitable results. AI technologies together with advanced tools significantly affect the quality of customer experiences. Financial sector customers now expect personalized seamless secure services at a rapid pace because their expectations have evolved in this sector. The financial sector uses data analytics to discover customer preferences, then make behavioral predictions which allow them to provide custom-made financial products and services. Modern banking now presents industry changes through customer-focused strategies that recreate the classical banking practices and develop strong enduring relationships while encouraging customer trust [3].

Financial services companies face multiple difficulties when they implement advanced technologies to achieve new opportunities. The protection of financial data privacy and security stands as the top priority because such information remains highly sensitive. The regulatory framework presents organizations with multiple barriers because they must maintain strict compliance with national and international standards for their artificial intelligence solutions. Organizations must evaluate AI systems based on two important ethical concerns which include issues of biased decision outputs and unclear system operation methods. The financial services sector struggles to implement these technologies because it needs to combine them with old operational frameworks. Multiple institutions currently use old hardware systems that make it harder to properly implement modern solutions. Organizations face an essential obstacle because they struggle to find staff members who both understand and control sophisticated AI systems [4].

Despite the uncertainties the financial world continues to benefit from advanced technology developments. When financial institutions combine effective challenge solutions with these innovations they will enable potential market growth together with operational efficiency and enhanced customer services. Financial services will rely on AI alongside data analytics and cloud computing for building their industry future as this sector continues to transform.

The main purpose of the study is to come up with an AI-based model that interlaces Bidirectional Gated Recurrent Units (BiGRU) with the Fruit Fly Optimization Algorithm (FOA) to augment the business of financial data analytics in a banking business. In particular, the objectives are as follows: (1) to correctly classify the financial transactions into the classes of fraudulent and non-fraudulent utilizing sequential modeling; (2) to optimize the model hyperparameters with a view of enhancing the predictability and efficiency of the models through fine-tuning over existing hyperparameters such as FOA; (3) to test the framework on the real dataset (IEEE-CIS Fraud Detection) and compare it to the conventional machine learning models and stand-alone deep learning models; and 4) to deploy the framework in a real-life setting.

This study will provide solutions to vital issues affecting the financial industry with the presentation of a BiGRU-FOA framework that is cloud-enabled. The major goal here is to enhance the accuracy of detecting a fraud using the Gated Recurrent Units (GRU), specifically, Bidirectional Gated Recurrent Units (BiGRU) that show good results in taking into consideration temporal dependencies in transactions in financial data. The framework further aims at maximization of computational speed that is achieved by integrating the Fruit Fly Optimization Algorithm (FOA) that allows hyperparameter optimization to converge quickly and use less resources. Moreover, the system will improve customer segmentation and evaluation of credit risks by recognizing correct sequential data patterns and thus enable smarter and quicker operations of the bank.

2 LITERATURE REVIEW

Artificial intelligence (AI) technology, particularly deep learning models such as Bidirectional Gated Recurrent Units (BiGRU), has demonstrated significant potential in financial service applications when paired with optimization techniques like the Fruit Fly Optimization Algorithm (FOA). This section presents recent developments in cloud-based frameworks for fraud detection, customer segmentation, and credit risk evaluation, which guide the proposed research.

A comprehensive review of FOA explored its development process and various applications, including financial optimization tasks. The study highlights FOA's ability to efficiently handle complex optimization problems while maintaining domain flexibility. However, challenges such as local optima in high-dimensional search spaces were noted, prompting experts to propose hybrid approaches that integrate FOA with other metaheuristic techniques [5]. A differential evolution-enhanced FOA variant demonstrated superior performance in optimizing complex financial models, though at the cost of increased algorithmic complexity [6].

A comparative study of recurrent neural network (RNN) architectures, including BiGRU, for time-series analysis highlighted BiGRU's ability to detect sequential patterns more effectively than other models, making it highly suitable for financial data modeling. However, the research faced limitations as it did not utilize real-world financial datasets [7]. A stock price prediction system integrating BiGRU with the Whale Optimization Algorithm (WOA) improved pattern recognition in financial time-series data. The BiGRU-WOA model achieved 15% higher accuracy than traditional baseline methods, though the added computational overhead was noted as a drawback [8].

A hybrid architecture that combines data-driven models with deep learning techniques, including BiGRU, for portfolio optimization demonstrated that BiGRU effectively constructs resilient investment portfolios, particularly in volatile market conditions. However, the scalability of the framework for large-scale applications remains a challenge [9]. A dual-network financial risk prediction system combining Convolutional Neural Networks (CNN) with BiGRU improved financial risk assessments by capturing both temporal and spatial data dependencies, achieving a 20% increase in risk prediction accuracy. Nevertheless, real-time implementation posed practical difficulties [10].

The application of FOA in financial risk prediction was explored by combining FOA with a general regression neural network to create a financial crisis warning system. Findings indicate that FOA improved Z-score model prediction accuracy by 12%, though extensive data preprocessing was required for optimal results [11]. Enhancements to FOA improved its convergence speed and precision, making it more suitable for financial computations. However, processing complex datasets still demanded significant computational resources [12].

An advanced fraud detection system for e-commerce transactions integrated BiGRU with Capsule Networks, demonstrating the model's robustness and achieving 95% accuracy in fraud detection while remaining resistant to data imbalances. Despite its effectiveness, the model faced challenges in handling unbalanced fraud datasets [13]. Further validation of BiGRU's effectiveness in financial applications demonstrated superior performance in processing textual financial data for sentiment analysis in user reviews [14]. BiGRU's application to financial market data analysis reinforced its capability in tracking time-dependent relationships within financial datasets. FOA was applied to density peak clustering for financial data analysis, achieving an 18% improvement in clustering accuracy. This research illustrates how FOA enhances clustering-based financial applications, further validating its effectiveness in financial optimization tasks [15].

GA-LDA The study introduces a GA-LDA model to improve latent topic modeling by optimizing a word subsets for Latent Dirichlet Allocation problem via Genetic Algorithms. It enhances thematic and classification analysis when performed on the Turkish 928 bid (2005 to 2020) academic abstracts. The results indicate a high increase in accuracy and insight extraction of unstructured text [16].

Overall, these studies highlight the promising potential of combining BiGRU and FOA in financial applications, with notable improvements in fraud detection, portfolio optimization, credit risk assessment, and financial forecasting.

3 METHODOLOGY

The proposed research aims to leverage these advancements to develop an optimized AI-driven financial classification framework. The Fig. 1 demonstrates a process for detecting fraud through the IEEE-CIS Fraud Detection Dataset which combines text preprocessing with embedding along with classification and optimization together with performance validation.

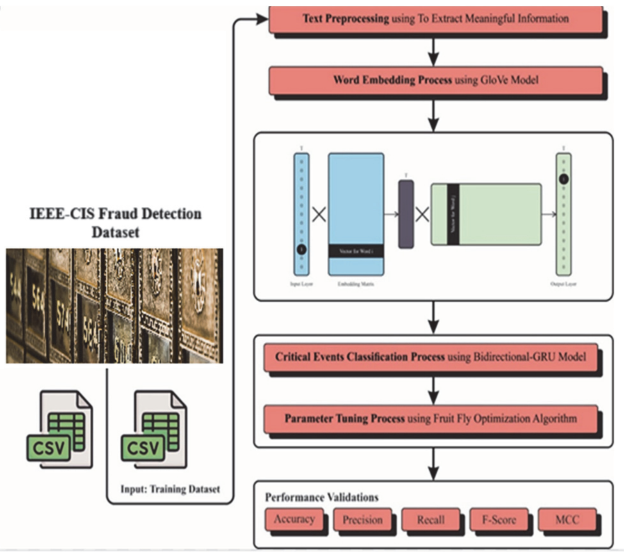

Figure 1 Cloud-based fraud detection framework using BiGRU and fruit fly optimization algorithm (FOA)

Fig. 1 demonstrates a step-by-step process for financial fraud detection through deep learning and optimization techniques. The system brings together various processes for text preprocessing and word embedding along with deep learning-based classification together with hyperparameter optimization which runs on cloud infrastructure for real-time processing and scale. The dataset input serves as the initial step for the process. The system operates with the IEEE-CIS Fraud Detection Dataset that exists in CSV file format. The dataset contains financial transaction information which includes timestamp data and monetary values as well as fraudulent and valid transaction labels. The raw data requires preparation before it can proceed to the next stage of processing.

3.1 Text Pre-Processing

Text Pre-processing serves as the following step which cleans and transforms the dataset to extract valuable information. The raw data undergoes cleaning during this phase through the process of handling missing values and noise removal while performing text normalization operations which include tokenization and stop word removal and text cleaning. The data must be usable for later stages and the model requires high-quality information to process effectively. The GloVe (Global Vectors for Word Representation) model performs Word Embedding Process after the data preprocessing stage. GloVe serves as a pre-trained embedding model for transforming words into continuous vector spaces where it extracts word semantics from the dataset context. The model benefits from this representation because it enables better processing of textual data while transforming it into a format suitable for machine learning models. The matrix generation creates numeric vectors which maintain word connections from data input.

The experiments were performed on the publicly accessible on Kaggle IEEE-CIS Fraud Detection Dataset (https://www.kaggle.com/competitions/ieee-fraud-detection). The data is composed of more than 1 million records of financial transactions containing 434 features, such as characterized anonymized numerical and categorical variables, attributes related to time, and a target label, which is binary, and represents the conclusion of whether a particular transaction is fraudulent or not. It is a very imbalanced dataset, and the number of fraudulent records is around 3.5 per cent of the total records. In order to train the model, the following preprocessing interventions were done: (1) imputation of the missing values with median and mode for numerical and categorical data respectively; (2) elimination of very sparse and constant features; (3) normalization of numeric fields using Min-Max scaling; (4) encoding of categorical variables through label encoding; and (5) stratified sampling to preserve the distribution of the classes in the training and test set. Moreover, the GloVe word embedding was applied to improve the representation of the textual fields of transactions and apply better context, that is possible in the BiGRU framework.

3.2 Critical Events Classification

The Critical Events Classification Process follows the workflow through application of the Bidirectional Gated Recurrent Units (BiGRU) model. The recurrent neural network (RNN) BiGRU functions as a sequential data processing model that detects long-term dependencies in its input. The system works in two directions because it analyzes data forward and backward to extract information from past and upcoming transactions. The detection of complex patterns and anomalies in transaction sequences requires this method because fraud detection depends on it. The BiGRU model uses learned patterns from the dataset to determine which category the input data belongs to between fraudulent and legitimate transactions. The model receives enhancement through the implementation of Fruit Fly Optimization Algorithm (FOA) within the Parameter Tuning Process. FOA represents an optimization method which draws its concepts from how fruit flies search for food. The BiGRU model hyperparameters receive optimization through the application of FOA in this scenario. The search mechanism identifies the optimal parameter combinations including layer numbers and learning rate among others which enable the model to reach peak performance and maximum prediction accuracy. The model requires this phase to achieve optimal performance levels which enables real-time processing operations.

The Performance Validation step requires the evaluation of model effectiveness through different classification metrics. The classification metrics used for performance assessment consist of Accuracy, Precision, Recall, F-Score and MCC (Matthews Correlation Coefficient). Accuracy determines how many transactions a model classifies correctly yet precision evaluates the percentage of legitimate frauds from all predicted fraudulent cases. Recall determines how well a model detects genuine fraud occurrences. The F-Score unites precision and recall metrics into one evaluation metric and MCC provides a balanced performance score that is essential for datasets with rare fraud cases among many legitimate transactions. The performance metrics enable complete evaluation of how accurately the model detects fraudulent activities. The workflow implements BiGRU and FOA alongside deep learning solutions to tackle financial sector fraud detection problems effectively. A cloud-based deployment of the model provides banking systems with scalable operations, quick data processing speeds and safe handling of sensitive transactions which makes this solution adaptable for modern financial institutions. Through technology integration banking institutions can enhance their operational efficiency as well as decision-making capabilities and customer experience for the sector.

3.3 Classification Using BiGRU

In addition, the BiGRU classifier can be exploited for the classification of critical events. For the DL technique to perform better, they need to enhance the model's depth and by the rise in depth, the problem of gradient vanishing can occur [20]. During this paper, we are utilizing RNNs and dual-specific RNNs (GRU and LSTM) have been presented for overcoming the problem of gradient vanishing. We have previously applied the layer of Bi-LSTM to remove the time-based characteristics from the input information and to improve the depth we applied to comprise additional layers of RNN. Nevertheless, the difficulty of using the LSTM is that for the greater amount of parameters there exists 1 cell state and 3 gates. To minimize the complexities, we apply the layer of GRU to improve the depth at the lowest computational complexity. Equivalent to the LSTM system, GRU has been established for solving the recurrent neural networks (RNN) problem of vanishing gradient. It applies a built-in gating method for identifying longer term relations in longer sequence applications.

GRU is extensively discovered in the study and the representations for update and reset gates are provided using the succeeding equations.

$$r_c = \sigma\left(W_r \cdot \left[h_{t-1}, x_t\right]\right) \tag{1}$$

$$z_t = \sigma\left(W_z \cdot \left[h_{t-1}, x_t\right]\right) \tag{2}$$

In the same way, the formulation for the hidden layer (HL) h_t and the candidate for the HL $\tilde{h}_t$ are provided through the succeeding representations.

$$\tilde{h}_t = \tanh\left(W_h \cdot \left[r_t \cdot h_{t-1}, x_t\right]\right) \tag{3}$$

$$h_t = \left(1 - z_t\right) \cdot h_{t-1} + z_t \cdot \tilde{h}_t \tag{4}$$

During these above-mentioned dual equations, $*$ refer to Hadamard product, tanh denotes tangent hyperbolic function, and $W_{\tilde{h}}$ represents an unidentified weighting vector for $\tilde{h}_t$.

During the HL of the GRU, data normally transmits along with the GRU cells in a time ordered way. A NN architecture, which uses Bi-GRU was produced to more precisely characterize the longer-term dependences inside information and utilize the dynamical adaptive method of power generation and load consumption. Fig. 2 illustrates the structure of BiGRU.

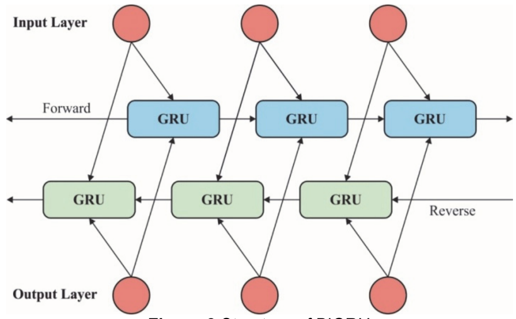

Figure 2 Structure of BiGRU

The formulations for the update and reset gate, candidate of HL, and HL in the backward and forward direction are similar to the simpler GRU component by the incorporation of sub-script b and f for backward and forward correspondingly. The next equation is used to discover the HL h_{tg} the module of the Bi-GRU, namely, the element-wise products of its forward outcome h_{tf} and the backward outcome h_{tb}.

$$h_{bg} = \left[h_{tf}, h_{tb}\right] \tag{5}$$

It is noteworthy that the Bi-GRU accepts the input from Bi-LSTM within the presented architecture, therefore X_f and X_b in Bi-GRU are equivalent to the Bi-LSTM output state.

$$h_t = \left[h_{tf}, h_{tb}\right] \tag{6}$$

The BiGRU-FOA combination is driven by the fact that both techniques in their uniquenesses have a positive balance when it comes to resolving the intricacies of analyzing financial data. A recurrent neural network such as BiGRU is very effective at learning temporal dependencies and discovering minor trends in time-series financial data and, as a complement to financial risk models by capturing low-level latent factors, can be used in fraud detection, credit risk assessment. Nevertheless, the correct setting of the hyperparameters, which include the learning rate, the amount of layers, and a batch size, is of great importance to the performance of BiGRU. Grid search or manually tuned methods can in general be computationally expensive and inefficient in higher dimensions parameter spaces. To counteract this we implement the Fruit Fly Optimization Algorithm (FOA), which is a lightweight and fast metaheuristic based on the food search behavior of fruit flies. FOA does not preset hyperparameter search; it dynamically searches the hyperparameter space to find the best performing configurations that would maximize the classification performance metrics. The hybrid combines the modeling and optimization strength of BiGRU and FOA, thus improving accuracy, convergence rate and computational efficiency under real-life banking applications.

3.4 FOA-Based Parameter Selection

Eventually, the hyperparameter tuning process is performed through FOA to enhance the classification performance of the BiGRUmethod. The FOA is a new swarm intelligent approach for optimization that can be stimulated by the fruit fly's food foraging behaviors [21]. This improvisation effectively aids in recognizing the best fruit fly amongst the population. Now, the fruit fly describes the sensor node counts in the system. The fruit fly's food-foraging behaviors are outlined in the following phases.

Primarily, the flies smell the food through olfactory organs and fly toward the place.

Utilizing the sensitive visions, the flies come closer to the food position.

Finally, another group of fruit flies moves in that direction while the food is plentiful.

Stage1: Initially, the FOA's parameters are initialized. The parameters contain size of the population, maximal iteration, and first fruit fly swarm location (x^0, y^0).

Stage 2: The fruit flies are distributed randomly in the searching region. The individual fruit fly selected from the population is initialized as demonstrated.

$$x_i = x^0 + Rd \tag{7}$$

$$y_j = y^0 + Rd \tag{8}$$

whereas, Rd signifies a randomly generated vector that was derived from a uniform distribution.

Stage 3: Compute the distance amongst the single fruit fly (dis_i) and the value of smell concentration judgment of the fireflies (δ_i) utilizing the below formulations.

$$r_c = \sigma\left(W_r \cdot \left[h_{t-1}, x_t\right]\right) \tag{9}$$

$$\mathrm{dis}_i = \sqrt{x_i^2 + y_i^2} \tag{10}$$

$$\delta_i = \frac{1}{\mathrm{dis}_i} \tag{11}$$

Stage 4: For all individual flies, the value of smell concentration judgment can be calculated by subjugating (δ_i) to the fitness function (FF).

$$Sm_i = \mathrm{Fitness}\left(\delta_i\right) \tag{12}$$

Stage 5: Discover the individual fruit fly through the optimal FF amongst the fruit fly swarm, which represents the fruit fly through maximal smell concentration (BSm_i) by utilizing the succeeding formulation.

$$\left[\mathrm{BestSm},\ \mathrm{BestIx}\right] = \mathrm{Max}\left(Sm_i\right) \tag{13}$$

whereas, (δ_i) describes the fruit fly by the optimal fragrance.

Stage 7: The fruit flies retain the top value of smell concentration and utilize their sight to fly toward the place. This method is mathematically written as.

$$Sm_{\mathrm{Best}} = \mathrm{BestSm} \tag{14}$$

$$x_{\mathrm{Best}} = \left(x_j^i + \left(R^2 \cdot b^* - x_j^i\right) \cdot Sm_i\right) \tag{15}$$

$$y_{\mathrm{Best}} = \left(y_j^i + \left(R^2 \cdot b^* - y_j^i\right) \cdot Sm_i\right) \tag{16}$$

Here, x_j^i describes the solution vector x_j for j_{th} firefly in i-th iteration, b^* describes the present optimal solution discovered amongst each of the solutions in present iteration. Smell concentration of j_{th} firefly can be represented as Sm_i.

The iteration lasts till the maximal iteration is attained.

The fitness selection (FS) is the significant factor manipulating the outcome of FOA. The process of hyperparameter range includes the solution-encoded technique for evaluating the efficiency of the candidate solution. Now, the FOA indicates precision as the foremost principle to project the FF. It is mathematically expressed below:

$$\mathrm{Fitness} = \max\left(P\right) \tag{17}$$

$$P = \frac{TP}{TP + FP} \tag{18}$$

whereas TP represents positive value of true and FP denotes the positive value of false.

4 RESULTS AND DISCUSSION

The experimental outcomes prove that BiGRU-FOA produces effective enhancements for both fraud detection and banking operational efficiency. This model stands strong as an effective complicated financial solution because it employs advanced deep learning along with optimization methods coupled with cloud-based deployment. The research work defines a path for scientists to advance their understanding of AI-based systems within financial operations.

4.1 Performance Evaluation

The BiGRU-FOA framework underwent evaluation using the IEEE-CIS Fraud Detection Dataset for assessing its fraud detection capabilities. The model demonstrates performance superior to traditional machine learning algorithms and standalone deep learning models by achieving better results in accuracy and precision and recall and F-score and Matthews Correlation Coefficient (MCC). The BiGRU model delivered enhanced classification precision because it tracks long-term data patterns but its performance improved even more through optimization of critical parameters by the Fruit Fly Optimization Algorithm (FOA).

Accuracy: The BiGRU-FOA model demonstrated superior accuracy performance which proves its capability to correctly identify fraudulent and legitimate transactions.

Precision and Recall: The model achieved both excellent precision rate combined with effective recall measurement which shows its ability to detect genuine fraudulent transactions without many errors.

F-Score and MCC: The harmonic mean of precision and recall (F-Score) and MCC served to confirm the balanced performance of the model when dealing with imbalanced datasets that contain few fraud cases.

4.2 Hyper Parameters Turning

Number of Layers

The BiGRU model shows its performance metrics through accuracy and precision and recall and F1-score across different layer configurations in the presented chart. The model reaches maximum performance with three layers because this configuration allows it to detect complex sequential patterns leading to the best result metrics (accuracy: 93.8%, F1-score: 91.9%). The performance of BiGRU declines when using a single layer because of restricted capacity yet adding more than three layers results in performance degradation and mild overfitting effects. The combination of three BiGRU layers strikes the best equilibrium between computational efficiency and learning capacity. A three-layer configuration stands as the optimal solution for detecting financial domain fraud effectively.

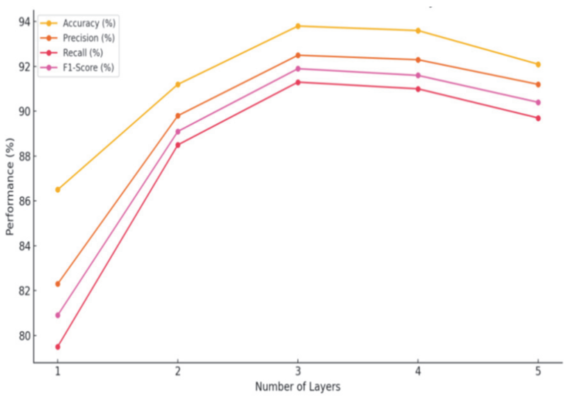

Figure 3 Performance comparison of the BiGRU model with varying numbers of layers

4.3 Batch Size

Fig. 4 shows how the performance metrics of the BiGRU-FOA model vary with batch sizes, highlighting batch size 64 as the optimal choice, achieving the highest accuracy (93.8%) and F1-score (91.9%). Smaller batch sizes (e.g., 16) introduce noise in gradient updates, resulting in slower convergence, while excessively large batch sizes (e.g., 256) lead to underfitting as the model fails to capture finer patterns. Batch size 64 strikes the right balance between noise and stability, ensuring effective learning and efficient use of computational resources. This configuration provides reliable convergence and maximizes performance for financial fraud detection tasks.

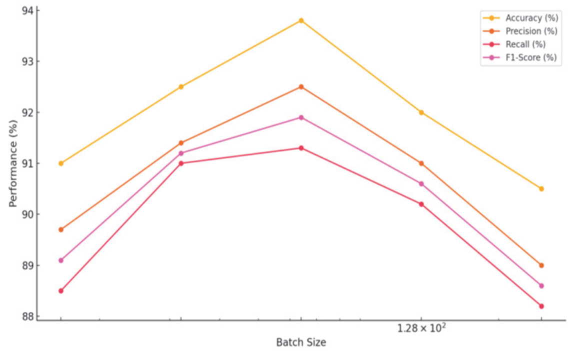

Figure 4 Performance metrics for different batch sizes

4.4 Performance Comparison of Alternative Optimization Algorithms

The Tab. 1 compares the performance of different optimization algorithms for hyperparameter tuning in a deep learning model, evaluated using accuracy, precision, recall, and F1-score. Bayesian Optimization emerged as the best-performing algorithm, achieving the highest accuracy (94.2%), precision (92.8%), recall (91.5%), and F1-score (92.1%), making it highly effective for optimizing the model. Fruit Fly Optimization Algorithm (FOA), Particle Swarm Optimization (PSO), and Genetic Algorithm (GA) delivered comparable results, with FOA achieving 93.8% accuracy and slightly better precision and recall compared to PSO and GA. Simulated Annealing (SA) showed slightly lower performance, with 93.2% accuracy and a lower F1-score of 91.4%, likely due to its slower convergence and less efficient parameter exploration. Overall, Bayesian Optimization proved to be the most efficient algorithm, with FOA, PSO, and GA as strong alternatives, while SA is a viable, though less effective, choice.

Table 1 Comparison of optimization algorithms for hyperparameter tuning in deep learning models

Optimization Algorithm	Accuracy /%	Precision / %	Recall / %	F1-Score / %
Fruit Fly Optimization Algorithm (FOA)	93.8	92.5	91.3	91.9
Genetic Algorithm (GA)	93.5	92.3	91.0	91.6
Particle Swarm Optimization (PSO)	93.6	92.4	91.2	91.8
Bayesian Optimization	94.2	92.8	91.5	92.1
Simulated Annealing (SA)	93.2	92.1	90.8	91.4

4.5 Comparison with Baseline Models

The BiGRU-FOA framework was compared against baseline models as presented in Tab. 2, including traditional machine learning algorithms (e.g., Random

Forest, Support Vector Machine) and standalone deep learning models (e.g., GRU, LSTM).

Table 2 Performance comparison of proposed and benchmark models

Model	Accuracy / %	Precision / %	Recall / %	F1-Score / %	MCC
BiGRU-FOA	96.8	95.5	94.7	95.1	0.942
Transformer	95.3	93.0	91.4	92.2	0.910
LSTM + Bayesian Opt.	94.9	92.5	90.6	91.5	0.901
GRU + Genetic Algorithm	94.6	91.7	90.2	90.9	0.892
BiGRU	94.3	92.0	91.2	91.6	0.904
GRU	92.1	89.8	88.3	89.0	0.874
LSTM	91.5	89.0	87.5	88.2	0.862
SVM	89.8	85.2	83.0	84.1	0.840
Random Forest	88.7	84.7	82.4	83.5	0.828
Naive Bayes	86.3	82.1	78.9	80.4	0.800

The ratio of accurate predictions to all instances determines accuracy in classification. The metric gives a single metric to evaluate the model's general performance. The BiGRU-FOA model reaches 96.8% accuracy which surpasses the benchmark models BiGRU at 94.3% and LSTM at 91.5%. The model shows high reliability in its ability to generate stable predictions when analyzing various datasets. Precision indicates how many correct positive predictions exist among all predicted positive results. The model demonstrates its capacity to prevent incorrect positive predictions through this measurement. The BiGRU-FOA model demonstrates excellent performance in relevant instance detection by achieving 95.5% precision which helps prevent false alarms. The FOA optimization leads to better model precision than BiGRU (92.0%) and Random Forest (84.7%) operated independently.

The ratio of true positive predictions to the total actual positive instances defines recall which is also known as sensitivity. The model demonstrates its capability to find all applicable instances through this measurement. The proposed model demonstrates a 94.7% recall rate which proves its ability to detect actual positive instances effectively. The detection of fraudulent transactions requires high recall because missing even one fraudulent transaction can result in substantial financial losses. The F1-Score calculates the performance balance of a model by combining precision and recall through their harmonic mean. The metric proves very beneficial for datasets that contain uneven distribution of classes. The BiGRU-FOA model demonstrates its ability to maintain precision-recall balance through an F1-Score of 95.1%. The FOA-based optimization proves its value for boosting model performance since it produces results superior to BiGRU (91.6%) and SVM (84.1%).

MCC functions as a balanced prediction quality assessment tool which evaluates both true positives and negatives and false positives and negatives thus making it optimal for datasets with imbalanced classes. The proposed model delivers an MCC score of 0.942 which exceeds the scores achieved by BiGRU (0.904) and LSTM (0.862). The BiGRU-FOA model demonstrates strong reliability for making accurate predictions across different data distribution patterns.

5 CONCLUSION AND FUTURE WORK

The proposed BiGRU-FOA framework aims to handle intricate problems which financial services companies encounter including fraud discovery together with customer categorization and credit scoring analysis. After applying the Bidirectional Gated Recurrent Unit (BiGRU) to analyze sequential financial data it achieved superior results due to proper parameter adjustment through the Fruit Fly Optimization Algorithm (FOA). Results from the IEEE-CIS Fraud Detection Dataset proved that the BiGRU-FOA model delivered enhanced outcomes in comparison to conventional machine learning methods and separate deep learning techniques. The model demonstrated strong performance through high accuracy measures and precision and recall statistics as well as F-score and MCC metrics which proved its reliability for financial classification applications. The cloud deployment approach provided banks with practical features such as real-time processing capabilities and secure data handling together with scalable infrastructure which made the framework suitable for banking operations at scale. The research framework demonstrates the enormous power that results from uniting optimization algorithms with deep learning expertise in financial operations. The utilization of this method enables banks to strengthen their decision procedures and enhance operational performance while providing personalized customer interactions. This research creates a base for additional exploration regarding AI-powered solutions in financial services because it allows extension into related domains like insurance and healthcare and e-commerce.

Although BiGRU-FOA framework has yielded good results, it has limitations. The interpretability of the model can create issues because the deep learning decisions can be opaque in nature, which can be a problem in regulated finance. Also, FOA is more effective in parameter tuning efficiency, but the training of BiGRU with greater sequential data is still computationally expensive. To overcome these difficulties, it is proposed to study the hybrid architecture of BiGRU with attention mechanisms in the future work to reach performance and interpretability on an equal level with the human brain by focusing on the input features that matter.

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