Identifying Abnormal Financial Transactions in E-Commerce: A Financial Statement Fraud Detection Model Using Op-BGRU and Modified Cheetah Optimization

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Abstract

Innovative cybersecurity developments are required to counteract growing cyber dangers caused by the exponential growth of Internet of Things (IoT) devices in entrepreneurial settings. This paper presents a method for detecting financial hazards in e-business commodity transactions using DL and CAD models; the goal is to investigate the detection of anomalous financial commodities in e-business. Because of issues with agencies, information asymmetry exists in all aspects of financial status, information, and reports; this poses a significant risk to the long-term viability of business operations and the efficiency of financial markets. This study takes a look at the financial and non-financial statistics of companies listed on the TWSE/TEPx from 2001 to 2019. Out of the 153 companies that were sampled, 51 reported financial statement fraud and 102 did not. To start, the dataset is cleaned up by doing normalization pre-processing. Financial fraud detection models are constructed by first selecting the most important features using the Modified Cheetah Optimizer. Then, the classifying process is carried out using the Optimized Bidirectional Gated Recurrent Unit (Op-BGRU) model. From what to can tell from the data, the suggested model performs better than the baseline RNN model across the board. This strategy will help in the fight against cybercrime and is a big step in the right direction toward arming entrepreneurs with the resources they need to thrive in the modern digital world. A safe, creative, and informed startup setting is what you get when you use sustainable IoT security measures.

Keywords: Optimized Bidirectional Gated Recurrent Unit; Internet of Things; Modified Cheetah Optimizer; Financial commodities; Entrepreneurs; Sustainable Security.

1. Introduction

The entrepreneurial ecosystem has been profoundly affected by the rise of IoT, which has caused a sea change in how companies function and come up with novel ideas. The importance of the entrepreneurial environment to economic growth and development has been extensively studied [1]. Studies have shown that entrepreneurial ecosystems boost value creation in local commercial operations by enhancing regional competitive advantages through innovation and expertise. Academics and politicians alike have taken notice of the entrepreneurial environment because of the good effects it has on company expansion and new venture formation [2]. There is evidence that the entrepreneurial ecosystem can help with resource allocation and encourage the launch of knowledge-intensive companies in areas with a strong demand for their services. In addition, the political climate is a major component influencing the entrepreneurial ecosystem performance of cultural enterprises operating on the Internet, highlighting the complex character of the ecosystem as a whole [3]. For more delicate entrepreneurial ecosystems, the multi-dimensional support offered by entrepreneurial colleges becomes even more important [4].

IoT effects on entrepreneurial ecosystems have been noted in many different industries, from traditional to digital, demonstrating the pervasiveness of IoT's impact on the very existence and functioning of firms [5]. At every stage of the customer lifecycle, businesses stand to gain from the IoT's influence on customer relationship management (CRM) systems [6]. Further highlighting the IoT's impact on entrepreneurial pursuits, it is crucial to the growth and acceptance of digital entrepreneurship at academic institutions. To have evaluated the effects of digital transformation on company presentation as a result of using big data and the IoT [7]. This review covers numerous important factors that lead to company success. Classifying the research problems to support the Internet of Things as a well-engineered, financially and technologically viable paradigm becomes more important as the effect of IoT on research domains increases [8]. This complexity is further highlighted by the fact that IoT integration into many business domains is not an easy task [9]. Government initiatives have highlighted the relevance of digital platform innovation, skill, knowledge, and entrepreneurship in policymaking, highlighting the role of the IoT in shaping governance and policy [10]. This paper presents an integrative research framework and a comprehensive overview of the most important research themes related to the IoT from a business and management standpoint. It emphasizes the need for a thorough understanding of how the IoT affects these fields [11]. Analysis showed that innovation, possibilities, and development impact the economy and the IoT, highlighting how the two are interdependent [12].

A company's financial status and operational results are detailed in its financial statements. Shareholders, investors, creditors, workers, and everybody else who uses accounting and financial reporting data relies on them as well [13]. Sometimes auditors and certified public accountants commit fraud. There are various forms of financial statement fraud, including (1) falsifying or altering accounting relevant evidence, (2) representing or omitting material info intentionally, and (3) using, recognizing, measuring, classifying, expressing, or disclosing relevant accounting principles in a willful and incorrect manner. First, chances and attitudes; second, incentives or pressure; and third, behavioral rationalization are the three main causes of fraud [14]. There is a strong correlation between financial declaration fraud and a company's eventual financial difficulties or insolvency, and this problem has far-reaching effects on macroeconomic and commercial activity levels, particularly for publicly traded corporations [15]. For certified public make more informed decisions and provide more reliable audit reports and views, it is critical to develop a reliable model for detecting fraud.

There is a lack of literature on the topic, but using algorithms to identify financial statement fraud seems like a good solution to overcome the limitations of the old method and take use of the age of big data and AI. When it comes to modeling, deep learning algorithms are formidable tools due to their ability to swiftly and efficiently process massive datasets. Deep learning models outperform and outperform manual or rule-based classifiers in terms of accuracy and performance. They don't necessitate the manual creation of classifiers or the manual writing of rules, and they can automatically adapt to different kinds of irregular financial items. The term "e-business" describes the process of doing business over electronic networks, including the World Wide Web and other social media sites. These days, e-business market data sets are too complicated, high-dimensional, and noisy for the old-fashioned econometric equation model or parameter model to handle. Deep learning (DL) is a significant subfield of machine learning that draws on inspiration from artificial neural networks and other areas. The original data is transformed from a low-level simple nonlinear model to a high-level abstract model using this feature learning method.

Therefore, the research is to build a model for detecting financial statement fraud using the robust and beneficial deep learning algorithm Op-BGRU. To top it all off, MCOA enhances classification accuracy by properly selecting key features. There are two types of variables used: financial besides non-financial, which are also called corporate governance variables. In raise users' knowledge of possible fraud besides help them recognize the symptoms of financial statement fraud, it is necessary to progress an efficient model for detecting such fraud. Losses caused by fraud should be mitigated and capital market sustainability should be preserved with this strategy.

This is the remaining structure of the paper: In Section 2, the relevant literature is reviewed. In Section 3, the organization that will be used is briefly described. Section 4 details the analysis that will be conducted. Finally, Section 5 offerings the conclusion.

2. Related works

An extensive bibliometric study of the IoT's use in banking and finance has been published by Judijanto et al., [16]. Key research issues, trends, also patterns in the subject are identified through a comprehensive examination and analysis of current literature. By employing bibliometric indicators like citation network analysis, co-citation analysis, and keyword co-occurrence analysis, one can map the domain's intellectual structure and discover new areas of attention and research. Additionally, the study offers suggestions for future research topics as well as practical consequences. The results provide researchers, politicians, and industry players with clues about how the IoT is changing the face of financial services.

According to research by Garg et al. [17], which examines the interplay between the platform provider's and app sustainability, the co-operative aspect of the IoT platform greatly influences the actions and earnings of both groups. Because of the interplay between network effects and economies of scale, a neutral newcomer to the platform boosts the effort levels of all current participants and the revenues. To also discover that a significant number of apps are required for the platform to viable, and that an even larger application base is needed for a less efficient platform leader. In order to keep the platform running, the platform breadwinner may need to offer more incentives to the app developers or even charge them more rent, depending on the amount of platform and who is more effective in the partnership. To also extract other intriguing findings and managerial insights, and To check our findings whether apps are competing or complementary. To discover, for instance, that current apps may benefit, under some circumstances, from the entrance of a competitive app.

In improve the quality of digital financial reporting, Nofel et al. [18] performed a comprehensive literature analysis on the topic of integrating blockchain technology, the IoT. Using the well-known PRISMA methodology, this research conducts a systematic literature review (SLR). This analysis drew its final sample from 309 relevant studies published between 2013 and 2023. Based on our research, it is clear that there is a dearth of literature discussing how to combine these three distinct technology into one cohesive AIS. Accounting stands to gain a great deal from this study's proposed new line of inquiry into the potential for combining the IoT, blockchain technology, and XBRL into a unified system. Still, it's easy to see how this connection may have positive effects, such as more openness, better data security, and the ability to generate reports in real time. The primary novelty of our paper is that, as far as To are aware, no other paper has investigated the possibility of integrating these three technologies before. Our work also helped to fill in some critical research gaps and suggest avenues for future studies that could spearhead investigations into the effects of this integrated system on accounting methods.

To that end, Qin and Zhu [19] set out to investigate the ways in which IoT alters the gathering, processing, and interpreting of financial data, among other facets of financial management. Findings from the study's comprehensive literature analysis, questionnaire survey, and experimental design indicate that sales, transaction times, and inventory control are all significantly improved by IoT technology. However, businesses must also take into account the initial investment required, concerns about data security and privacy, and other obstacles when implementing these technologies. When it comes to financial management, IoT technology offers a lot of possibilities, but before applying it, firms should weigh all of the risks and rewards.

Using Boolean operatives and the terms "IoT," "Big Data," "H IoT," besides "AI," Santhanagopalan et al., [20] has retrieved results from the Scopus database. Two sections make up the chapter. The primary focus of the first section is a review of the relevant literature. Part 2 delves into the ways AI is being used in a range of industries, including healthcare, education, banking, smart cities, energy, communications, and agriculture. A review of the relevant literature reveals that ML, big data, and the Things will play critical roles in the future. The writers of this chapter urge academics, businesses, and governments to hold conferences, seminars, and cooperative initiatives in order to digitize all facilities and implement data-driven decisions.

The security flaws that come with Internet of Things devices have been studied by Harkai et al., [21]. These flaws include insufficient authentication, infrequent software upgrades, and malware vulnerability. Because of these flaws, hackers might potentially gain access to smart homes and steal money or personal information. The risk also grows due to the interconnected nature of the IoT ecosystem, since a hacked device might open the door to a larger network intrusion. This problem is made worse by the fact that there are no established regulatory frameworks or defined security protocols. Consequently, in order to mitigate these dangers, it is imperative that manufacturers, regulatory bodies, and users work together to set strong security standards. This way, any risks can be reduced and the security of smart home financial transactions can be improved.

Case studies of four companies that have created SCF keys in agricultural service supply chains that are blockchain enabled were comprehensively examined by Bhatia et al., [22] using the Context-Intervention-Mechanism- paradigm. The results demonstrate that SCF solutions enabled by blockchain can lower transaction costs across the board, including those related to information search, contracting and negotiation, and accessing financing. Different solutions will be developed with different primary goals. For example, solutions aiming to improve farmers' financial conditions will differ from those decreasing process inefficiencies. By outlining operational hurdles and providing tangible answers to these issues, the study's findings will be businesses looking to build and use blockchain-enabled SCF solutions.

Dong et al., [23] presented a method for predicting power that relies heavily on data mining techniques like deep learning, decision trees, and neural networks. Financial data can be analyzed using these techniques to identify trends, patterns, and anomalies that may indicate fraud, mistakes, or other irregularities in the future. Businesses can mitigate possible financial losses by promptly recognizing and responding to these irregularities. The capability of AI to handle and evaluate massive volumes of complicated data reflects its significance in the financial management of businesses. With the use of AI, businesses may streamline and improve the accuracy of their financial operations by automating tasks like invoice processing and reimbursement administration. In this work, to apply an ARIMA regression model, which is based on an AI deep learning algorithm, to forecast financial anomalies and trends in enterprises' financial development. This will aid enterprises in risk management and investment as well as in coping with and capitalizing on investment opportunities.

3. Proposed Methodology

The financial statement fraud detection model is built using optimizer models and deep learning algorithms that are fed both financial data. Both models are well-suited for the model building process depicted in Figure 1 and can efficiently handle massive amounts of data. The following is a description of each block based on that figure:

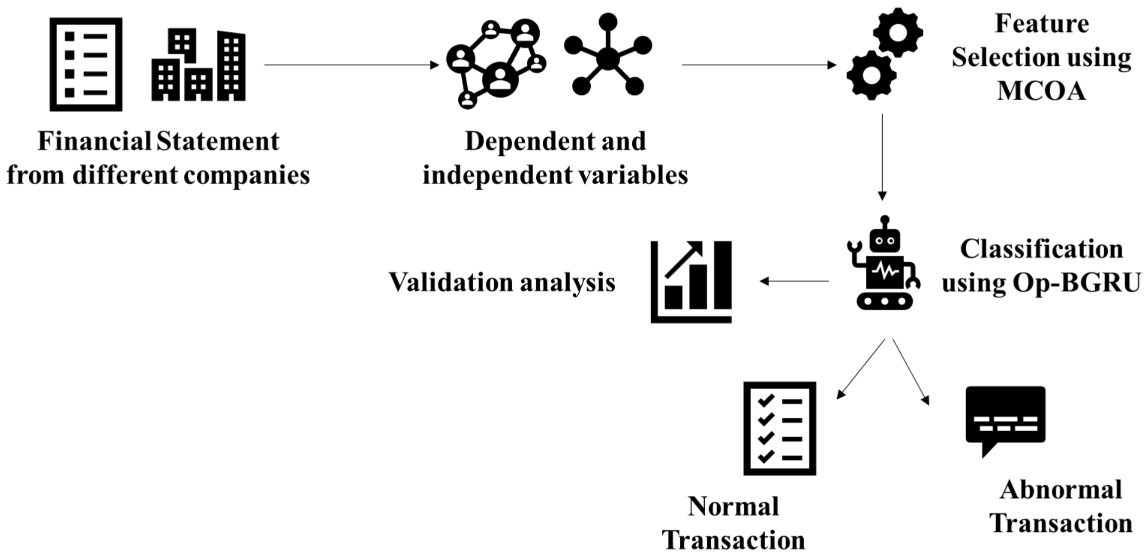

Figure 1: Workflow of the Proposed model

3.1. Dataset Description

A total of 153 businesses listed on the TWSE/TPEx between 2001 and 2019 are included in this analysis. Of the enterprises in the study, 51 have reported instances of financial statement fraud, whereas 102 have not [24]. From 2001 to 2019, this study takes a example of the listed on the TWSE/TEPx. A total of 153 companies are sampled once incomplete data is deleted. The ratio of companies reporting financial statement fraud to those not reporting is 1:2, meaning that 51 companies have reported financial statement fraud while 102 have not. Taiwan Economic Journal (TEJ) is the source for both financial besides non-financial data. Table 1 summarizes the industries that were sampled.

Table 1. Summary of sampled Industries.

Industry	Non-FSF	FSF	Total
Food	6	3	9
Textile	6	3	9
Computers besides peripherals	4	2	6
Optical electronics	12	6	18
Wire besides networking	4	2	6
Electronic components	8	4	12
Consumer electronics waterways	4	2	6
Information services	10	5	15
Plug-in machinery	6	3	9
Appliances besides electric cables	6	3	9
Medicine besides biotech	4	2	6
Steel	4	2	6
Other electronic divisions	8	4	12
Building materials and construction	2	1	3
Cultural and creative industry	2	1	3
Others	6	3	9
TOTAL	102	51	153

3.2. Research Variables

3.2.1. Dependent Variable

A dummy variable representing the dependent variable takes on the values 1 for companies who disclose financial companies that do not.

3.2.2. Independent Variables (Research Variables)

In order to quantify fraud, this research uses a set of 18 commonly utilized variables. Included in this set are fourteen financial variables and four variables that pertain to corporate governance. Table 2 summarizes the study variables.

Table 2. Research variables.

Variable Definition or Calculation	Variable Name	Code
Ln (aggregate liabilities)	Liability (natural logarithm)	X01

Current assets ÷ current liabilities	Current ratio	X02
Quick assets ÷ current liabilities	Quick ratio	X03
Liabilities ÷ shareholders' equity	Liability/equity ratio	X04
Liabilities ÷ assets	Liability ratio	X05
Net income equity	Return on equity (ROE)	X06
[The sum of net income, interest expense, and income tax divided by one minus the tax rate] the mean value of all assets	Return on assets (ROA)	X07
The equation for plant, property, and equipment is (long-term liabilities + shareholders' equity).	Long-term capital acceptability rate	X08
Cash ÷ assets	Cash as a percentage of assets	X09
Net income ÷ assets	Net income/assets	X10
Gross profit ÷ revenue	Gross margin	X11
Non-current liabilities ÷ total assets	Non-current liabilities/belongings	X12
Income minus the amount of cash flow from operations	Net flows from operating accomplishments/revenue	X13
1 for net loss and 0 for net income	Net loss or not	X14
Total number of directors in charge Board seat count	Percentage of managing directors	X15
At the end of the term, the number of ordinary shares outstanding divided by the number of shares held by large shareholders	Percentage of shares held by officer shareholders	X16
Number of shares owned by supervisors and directors ÷ As of the period's conclusion, the number of ordinary shares in circulation	The proportion of stock owned by executives besides managers	X17
The formula is premeditated by dividing the number of shares pledged by directors and supervisors by the number of shares held by them.	Measurement of shares pledged by directors besides supervisors	X18

3.3. Data pre-processing

As a preprocessing step in the suggested prediction framework, Min-Max normalization can be used to scale numerical features within a given range. By making sure all features are on the same scale, this normalization method stops features with big magnitudes from stealing the show during model training. In Eq. (1), the Min-Max normalization looks like this:

$$X_{normalized} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

Where X is the original charge of the feature, X_{max} is is the maximum charge of the feature in the dataset. It is possible to normalize each numerical feature separately using Min-Max. To improve machine learning model convergence and performance, the suggested architecture includes Min-Max normalization in the data preprocessing pipeline. This ensures that feature scales are consistent. Improved prediction accuracy and faster model training are both outcomes of Min-Max normalization, which involves reducing the feature sizes to a similar range.

Maintaining the quality and dependability of the input data for the proposed model was dependent on preprocessing procedures that dealt with missing values and ensured data integrity. When numerical data was missing, imputation methods like mode, median, or mean were used to replace the gaps without introducing bias. When categorical data was missing, the most frequent value was used. To interpolate between known values or propagate the last observed value, time-series data was filled in either forwards or backwards. To further guarantee data integrity, To used normalization techniques like Min-Max standardization to uniformly data and ran thorough data validation checks to find and fix any outliers or anomalies before feeding it into the model. For the suggested model to perform well in the prediction tasks, it is essential that the input data be clean, consistent, and robust; these preprocessing processes achieved just that.

3.4. Feature Selection using MCOA

The most relevant features from the Table 2 are selected by MCOA in this work, where the basic introduction of COA is discussed as follows:

3.4.1. Basic Introduction of CO

Taking cues from cheetah hunting tactics, the CO algorithm is a novel meta-heuristic optimization method [25]. It has many benefits, such as simplifying calculations, obtaining convergence quickly, and requiring little adjustments to the parameters. Searching, waiting, and attacking are the three main steps of the algorithm.

1) Searching Stage

In order to choose food that is suitable for the current weather and other factors, a cheetah meticulously surveys its environment, making use of its excellent vision and knowledge of hunting techniques. Here is the mathematical model at this stage:

$$P_{i,j}^{t+1} = P_{i,j}^{t} + Rd.\, a_{i,j}^{t} \quad (1)$$

$$a_{i,j}^{t} = 0.001 \times \frac{t}{T}.\left(U_j - L_j\right) \quad (2)$$

where $P_{i,j}^{t}$ and$P_{i,j}^{t+1}$ characterize the cheetah i at repetition t, correspondingly; Rd is a random sum nominated from the intermission (0, 1); $a_{i,j}^{t}$ is length; U_j besides L_j characterize the bounds of variable j, correspondingly; t and T denote the current and extreme repetition statistics.

2) Sitting and Waiting Phase

The cheetah's every step while foraging puts it in danger of rousing its prey, which could lead to its escape. The cheetah avoids this danger by keeping low to the ground or hiding in the underbrush. They wait for their victim to get dangerously close before attacking. It is possible to express the cheetah's position mathematically as follows while it is in the sitting and waiting period:

$$P_{i,j}^{t+1} = P_{i,j}^{t} \quad (3)$$

3) Attacking Stage

Cheetahs depend on their exceptional speed and agility to successfully hunt, and they are famous for excellent timing in attacking their prey. While attacking, the cheetah uses its tremendous speed to get very close to its target, covering a lot of ground in a short sum of time. To guarantee a successful capture, the cheetah strategically puts its prey in precarious settings, capitalizing on its agility. These assaults might happen singly or in clusters. The cheetah's positioning during a solo assault is carefully adjusted to follow the movements of its victim. Cheetahs adopt this same interactive strategy when attacking in groups, taking into consideration the prey's behavior and the status of their fellow group members. The following is the mathematical representation of the model for this phase:

$P_{i,j}^{t+1} = P_{H,j}^{t} + A_{i,j}.B_{i,j}^{t}$ (4)

$A_{i,j} = |R_{i,j}|^{exp\left(\frac{R_{i,j}}{2}\right)}.sin(2\pi R_{i,j})$ (5)

$B_{i,j}^{t} = P_{k,j}^{t} - P_{i,j}^{t}$ (6)

where t and T denote the current numbers; $P_{H,j}^{t}$ signifies the prey's position; $A_{i,j}$ revolving factor; $R_{i,j}$ signifies a random nominated from a normal distribution.; $P_{k,j}^{t}$ and $P_{i,j}^{t}$ represent the sites of cheetah k besides cheetah i at repetition t, correspondingly. The parameter value of CO and MCO algorithms are shown in Table 3 respectively.

Table 3. Parameter settings of diverse procedures.

Algorithms	Parameter settings
CO	$Rd = random(0,1)$
	$R_1 = 0.42$
MCO	$Rd = Tent$
	$R_1 = 0.42$

3.4.2. MCO

The optimization efficacy was enhanced following the modification of the standard CO algorithm. What follows is a comprehensive plan for enhancement.

1) Searching Strategy

Following the overview of mapping [26], the cheetah was initialized using the Tent chaotic map instead of the regular CO's randomly generated technique. This leads us to the following possible changes to Eq.(1)::

$P_{i,j}^{t+1} = P_{i,j}^{t} + T_c^T$ (7)

$$T_c^T = \begin{cases} \frac{T_c^{t-1}}{\gamma}, & T_c^{t-1} \in [0,\gamma] \\ \frac{(1-T_c^{t-1})}{(1-\gamma)}, & T_c^{t-1} \in [\gamma,1] \end{cases} \quad (8)$$

where t represents the current repetition; $\gamma \in (0,1)$.

2) Attacking Strategy

In this part of the process, the cheetah keeps its position updated using the dynamic weighting factor Σ. The cheetah is able to perform an efficient global search because λ is given a greater value at the start of the iteration. As the iteration nears its conclusion, λ adaptively declines. This allowed us to make the following adjustments to Eq.(4).:

$P_{i,j}^{t+1} = P_{H,j}^{t} + \lambda_{i,j}.B_{i,j}^{t}$ (9)

$\lambda = \frac{e^{4(1-\delta)} - e^{-4(1-\delta)}}{\left[e^{2(1-\delta)} + e^{-2(1-\delta)}\right]^2}, \delta = \frac{t}{T}$ (10)

$B_{i,j}^{t} = P_{k,j}^{t} - P_{i,j}^{t}$ (11)

After selecting the most relevant features from the MCOA, the input data is given to the classifier for prediction stage that is explained in the next section.

3.5. Op-BGRU Diagnostic Model for Abnormal detection

3.5.1. Gated Recurrent Unit Neural Networks

The gated recurrent unit neural network (GRU) was created in early 2014 and combines the best features of the RNN and LSTM models; as a result, it is better able to compute time series and integrate correlations between different sets of data. Additionally, it eliminates the issue of gradient explosion during LSTM computation by merging the forgetting and input gates into a "update gate," which simplifies the model structure and reduces the training parameters, thus improving computation efficiency and decreasing computation time. Sigmoid activation function (A) is depicted in Figure 2, which shows the GRU model's network architecture.

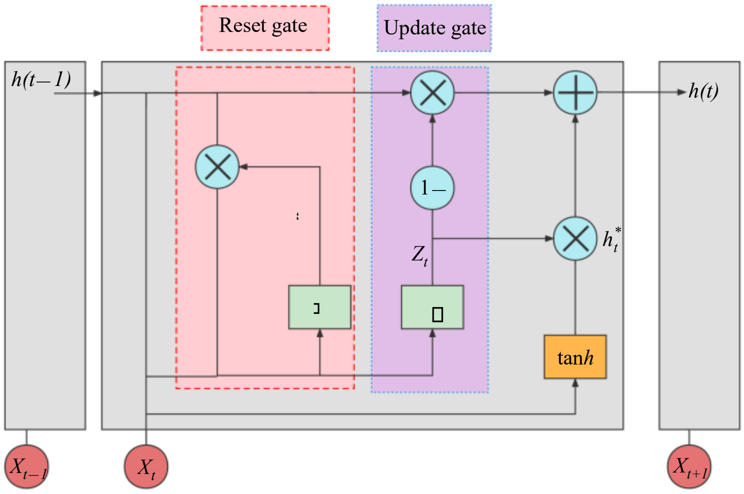

Figure 2. The network construction of the GRU perfect.

The updated equation for the limits of the GRU classical is

$$\begin{cases} r_t = sigmoid(W_r X_t + U_r h_{t-1} + b_r) \\ z_t = sigmoid(W_z X_t + U_z h_{t-1} + b_z) \\ h_t^* = tanh(W X_t + r_t U h_{t-1} + b) \\ h_t = (1 - z) h_t^* + z_t h_{t-1} \end{cases} \quad (12)$$

where: X_t signifies the input at moment t; sigmoid besides functions used to compute the output of layer neurons; r and z characterize the reset gate besides update gate, correspondingly; W and U are both matrices of GRU; b represents the bias; h_t^* denotes the candidate layer; h_t layer; r_t symbolizes a moment in period when the reset gate hidden state h_{t-1} to control the influence of the contender state h_t^* so that any immaterial evidence found in the future can be successfully discarded; and z_t denotes a moment in gate info in the state h_{t-1} can be accepted to the currently hidden state h_t.

When the current output is solely tied to one previous state variable, the GRU's unidirectional, back transmission state is typically employed to address this issue. As a result, a bidirectional GRU classical will improve the accuracy of diagnoses by eliminating confounding variables.

3.5.2. The BGRU Model

The output is dictated by the combined states of the two unidirectional GRUs that make up the BGRU, which is layered on top of each other. Figure 3 displays the model network architecture.

In Figure 3, X_i indicates the abnormal data besides the external conditions input data; e_i signposts the vector input data X_i; $\overrightarrow{h_\iota}$ designates the hidden layer direction; besides $\overleftarrow{h_\iota}$ signposts the state in the opposite direction.

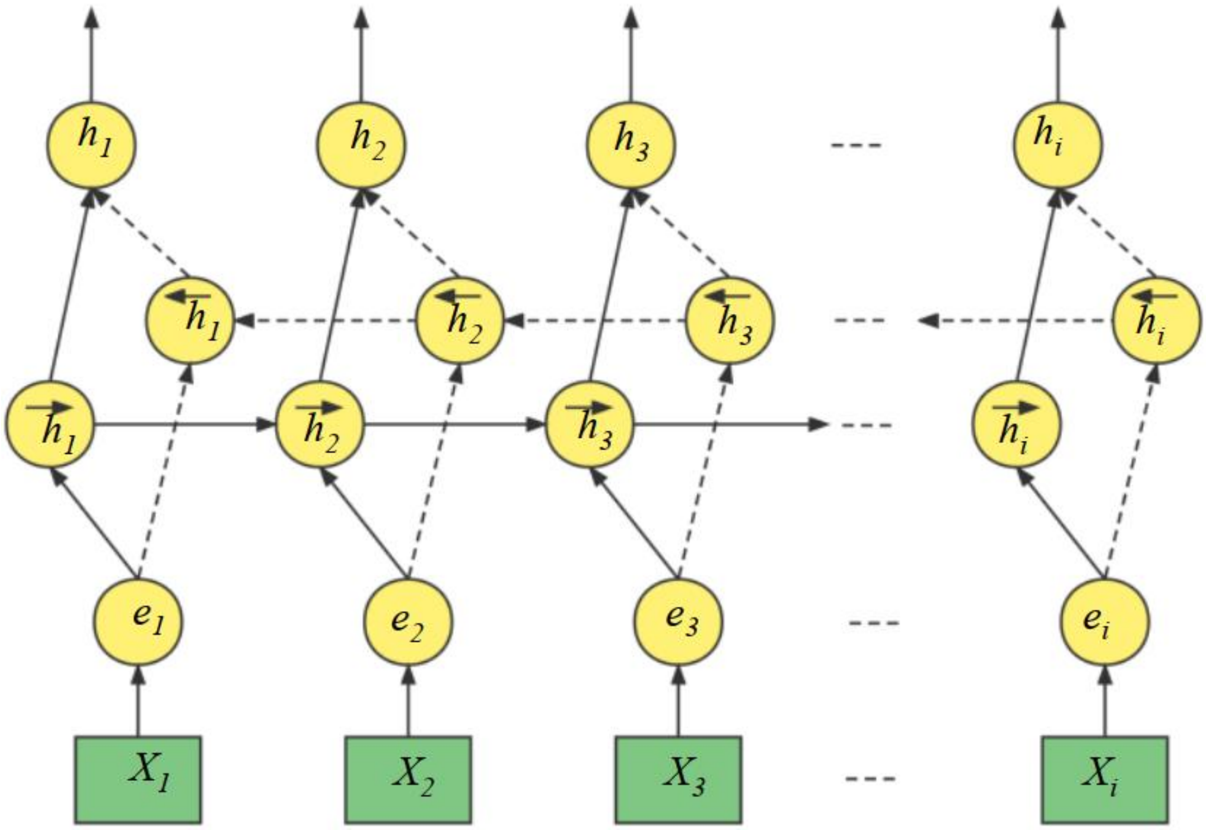

Figure 3. The network structure of the BGRU model.

3.5.3. Hyper parameter tuning using Elk Herd Optimizer (EHO)

This work uses EHO to hyper-tune BGRU's parameters [27]. To incorporate the elk herd breeding cycle into the optimization framework, the EHO mathematical model suggests six procedural stages. To will go over these processes in detail.

Step 1: Initialize Parameters of EHO and optimization difficult.

Both the goal function for evaluating the solution besides the solution illustration that clarifies the type of search space are essential for embedding problem-specific knowledge within the EHO. Optimization issues with incessant search spaces, where variable has a specific value range, are typically simplified versions of these problems. The goal function can be uttered generally in the method of Eq. (13).

$$\min_{x} f(x)\ x \in [lb, ub] \tag{13}$$

where $f(\boldsymbol{x})$ objective role used to degree the elk or key $x = (x_1, x_2, \dots, x_n)$. The variable x_i in each elk refers by i where $x_i \in [lb_i, ub_i]$ in which lb_i is bound, and ub_i is bound for the attribute x_i.n is total sum of attributes in every one dimensionality.

The EHO is limit, which is the bull rate B_r, which establishes the elk herd's first bull birth rate. Elk herd size, also known as population size (EHS), and maximum iterations are the other two conventional parameters. (M_Itr).

Step 2: Generate the initial elk herd

At first, a populace of elk keys, including males besides harems, is formed; this is called the elk herd (EH). According to Eq. (14), matrix with dimensions n×EHS.

$$\mathrm{EH} = \begin{bmatrix} x_1^1 & x_2^1 & \cdots & x_n^1 \\ x_1^2 & x_2^2 & \cdots & x_n^2 \\ \vdots & \vdots & \cdots & \vdots \\ x_1^{EHS} & x_2^{EHS} & \cdots & x_n^{EHS} \end{bmatrix} \tag{14}$$

In domain, each solution x^j can be produced as $x_i^j = lb_i + (ub_i - lb_i) \times U(0,1),\ \forall i = 1,2,\dots,n$. After determining the every elk key using Eq. (14), the elks in EH are arranged in ascending order according to their fitness ideals, for example, $f(x^1) \leq f(x^1) \leq \cdots \leq f(x^{EHS})$.

Step 3: Rutting season

The EHO is used during rutting season to engender families according to the bull rate. (B_r). First, the sum of all families is determined by multiplying B_r by EHS and then dividing by B. According to Eq. (15), the bulls are chosen from EH by looking at their fitness values. The elks from numbing B that have the best fitness painstaking bulls. The strongest elks will be given more harems as a reflection of the combat dominance challenges.

$$\mathcal{B} = \arg \min_{j \in (1,2,\dots,B)} f\left(\boldsymbol{x}^j\right) \tag{15}$$

After that, the bulls in set B are battling it out to start families. Each bull in B is given a harem according to its fitness value, which is a percentage of the value; this selection process is called the roulette-wheel selection. Technically speaking, the first thing that every bull x^j in $\mathcal{B}$ will be assigned with a assortment likelihood p_j based on its total fitness charge $f\left(x^i\right)$ divided by the summary of absolute fitness standards in Eq.(16).

$$p_j = \frac{f\left(\boldsymbol{x}^j\right)}{\sum_{k=1}^{B} f\left(\boldsymbol{x}^k\right)} \tag{16}$$

The second step is to use the selection probability p_j from Algorithm 1 to determine which bulls will get which harems. The vector is algorithm$H = (h_1, h_2, \dots, h_k)$, $k = EHS - B$ represents the herds, with each one allocated by the bull index that is decided using a roulette wheel.

For specimen, if the elk ten $(EHS = 10)$, besides the bull proportion is 30%, then $B = 3$, which reflects the sum of families. The $\mathcal{B} = (x^1, x^2, x^3)$. The elks (i.e., $(x^4, \dots, x^{10})$) might be pointed as harems, and their distribution could be strong-minded by spinning a roulette wheel. Then, could be $H = (1,2,1,3,1,2,3)$, with the first bull having three bull having two, and the third bull having two.

Step 4: Calving season

In season, the calve $\left(x_i^j(t+1)\right)$ of each copied based attributes mostly extracted bull $\left(\boldsymbol{x}^{h_j}\right)$ besides mother harem $\left(x_i^j(t)\right)$.

In case the calf $(x_i(t+1))$ has the similar catalogue i as its bull family, the calf is duplicated as shown in Eq. (17).

$$x_i^j(t+1) = x_i^j(t) + \alpha \cdot \left(x_i^k(t) - x_i^j(t)\right) \tag{17}$$

where α is a haphazard charge within the variety of [0,1] that controls the rate of the congenital attributes from the arbitrarily designated elk herd $x^k(t)$ where $k \in (1,2,\dots,EHS)$. Kindly be informed that as α increases, the possibility of random factors calf increases, leading to better diversity.

In case the calf has the mother, then it $\boldsymbol{x}_i(t+1)$ earnings the qualities of harem $\boldsymbol{x}^j$ besides father bull $\boldsymbol{x}^{h_j}$ as formulated in Eq. (18).

$$x_i^j(t+1) = x_i^j(t) + \beta\left(x_i^{h_j}(t) - x_i^j(t)\right) + \gamma\left(x_i^r(t) - x_i^j(t)\right) \tag{18}$$

where $x_i^j(t+1)$ is the attribute calf j at restatement $t+1$ which stowed in EH'. The h_j is the bull harem j, besides r is the guide of a accidental that $r \in \mathcal{B}$. In countryside, in a few cases, the mom harem can additional instructions, if it is not fortified thriving by its bull. γ and β are values among zero and two that are used at random to determine what parts of the traits are passed down from parents to offspring.

The coefficients β and γ, which are similar to models in the PSO, may serve as important parameters in the suggested EHO, as can be shown from Equation 18. The significance of both the'social' besides 'cognitive' factors for PSO's effectiveness has been proven in experiments, and as a result, many other researchers have followed suit in their published papers. Another thing to keep in mind is that using arbitrary values for β and γ within the range of [0,2] instead of fixed values could potentially lead to better performance in certain optimization issues. Reason being, within the given range, arbitrary numbers for β and γ show promise in attaining a commendable degree of EHO performance. By balancing EHO's global and local search skills, β and γ are shown to be effective.

Step 5: Selection season

There has been a merging of all families' bulls, calves, and harems. To put it technically, the EH that contained the solutions for the bulls besides harem and keys for the calves are combined into a single matrix. $\mathrm{EH}_{\mathrm{temp}}$. The elks in the EH_{temp} will be arranged in climbing on values. Finally, elks of the totalling EHS in $\mathrm{EH}_{\mathrm{temp}}$

Calves' reproduction will be kept to the next generation where elks in EH, such that $\mathrm{EH}^j = \mathrm{EH}_{\mathrm{temp}}^j, j = (1, \ldots, EHS)$. The term used to describe this form of selection in evolutionary theory, where ν represents the parent populace and λ represents the progeny population.

Step 6: Termination measures

Returning to stages $3, 4, besides\ 5$ will default behavior if the criteria is not met. As a stopping point, the maximum iterations is occasionally employed. The optimal solution may be within reach, the maximum amount of perfect iterations may be, or the computing time may be at its highest.

3.5.4. Steps for the EHO to Find the Optimal BGRU Limits

In order to make BGRU's classification more precise and useful in real-world scenarios, the EHO approach was employed. Batch size (EHO), alpha, the sum layers of organizational parameters, besides the number of layer are a few of the hyperparameters in the BGRU model that significantly affect the prediction accuracy. Table 4 displays the search intermissions for the key BGRU hyperparameters.

Table 4. BGRU Hyperparameter Optimization Intermissions.

Scope of the Search for Fineness	Limit
[0, 300]	EHO
[0.001, 0.05]	alpha
[1, 100]	num

The steps for the EHO to invention the optimal BGRU strictures are as shadows.

Step 1: The maximum sum of iterations should be set to Tmax, the search space dimension to D, besides the size of the EHO to N. You can enter a range of standards for the BGRU training parameters, including batch size (EHO) besides (alpha). Quantity of hidden layers (num) and sum are structural characteristics that can take on a variety of values. Make a note of the set of parameters for η = {EHO, alpha, $[num1, \ldots, numn]$}.

Step 2: Separate the decrease into a set besides set after using the MCHOA way to features from the data.

Step 3: Put together the Op-BGRU scheme. Find the precision and use it as the EHO's fitness function. The ratio to indicates the model's accuracy.

Step 4: Recalculate the EHO individuals' fitness value. Ascertain if the present fitness value has reached the supreme value or the concentrated sum of iterations. Assign the best set of parameters, denoted as ηbest, to BGRU if the criterion is met. Proceed to step 3 if not.

Step 6: Build the suggested Op-BGRU model using the EHO optimized parameters. After BGRU has the best possible parameters, it will begin the diagnostic tasks and report back the outcomes, which will include the algorithm's accuracy, classification, and running time.

4. Results and Discussion

To conduct the research, a computer with an $Intel\ Core\ i5-7200\ processor$ besides 8 GB of interior memory is utilized. The processor is accomplished of running at 2.7 GHz. A 64-bit version of Windows 10 with a specialized user interface (UI) and the Jupyter Notebook (Python 3.7) atmosphere are utilized to execute the operations. Here, to compare the suggested model's performance to that of preexisting modes using a variety of criteria, as illustrated visually in Figures 4 and 5.

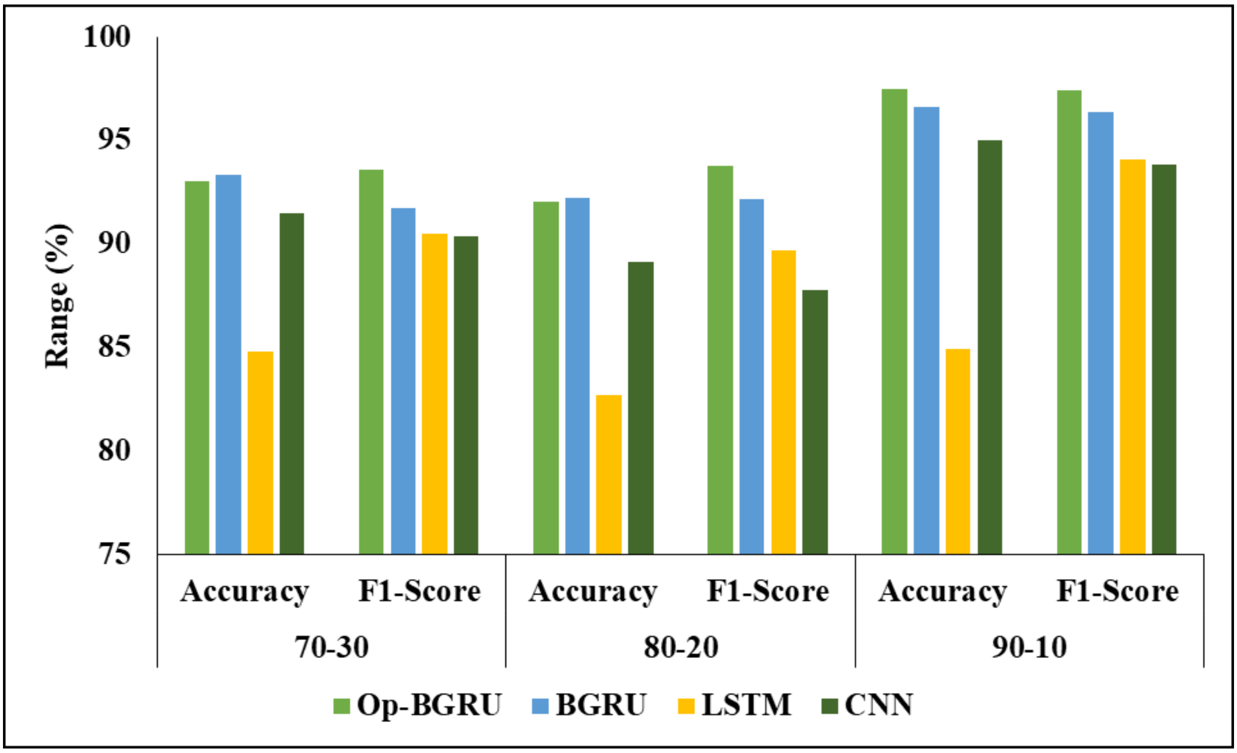

Figure 4: Graphical Comparison of proposed model

Compares the Op-BGRU, BGRU, LSTM, and CNN models' performance across three data splits—70-30, 80-20, and 90-10—evaluated using Score metrics. In the 90-10 split, Op-BGRU realizes accuracy of 97.5%, precision of 98.0%, recall of 96.2%, besides an F1-Score of 97.40%, showcasing its overall superior performance. BGRU also performs well in this split, with an accuracy of 96.6%, %, recall of 98.1%, besides an F1-Score of 96.37%. In contrast, LSTM underperforms with an accuracy of 84.9%, precision of 75.0%, but achieves a high recall of 98.1% besides an F1-Score of 94.07%, indicating its strength in identifying relevant cases despite lower precision. CNN records accuracy of 95.0%, precision of 91.1%, recall of 98.1%, besides F1-Score of 93.83% in the 90-10 split. In the 80-20 split, Op-BGRU achieves 92.0% accuracy, 92.9% precision, 88.8% recall, besides F1-Score of 93.74%, slightly outperforming BGRU, which records 92.2% accuracy, 94.0% precision, 88.2% recall, and a 92.17% F1-Score. For the 70-30 split, both Op-BGRU and BGRU maintain solid results with Op-BGRU achieving 93.0% accuracy, 91.4% precision, 92.5% recall, and 93.57% F1-Score, while BGRU follows closely with 93.3% accuracy, 92.0% precision, 92.7% recall, besides a 91.69% F1-Score. LSTM and CNN in the 70-30 split achieve lower accuracy of 84.8% and 91.5%

respectively, with LSTM showing lower precision at 76.6% but a high recall of 93.6%, while CNN records a balanced precision and recall (89.1% and 91.7%) with an F1-Score of 90.36%. Overall, Op-BGRU demonstrates the most consistent high performance across all splits, followed closely by BGRU, particularly excelling in accuracy and F1-Score.

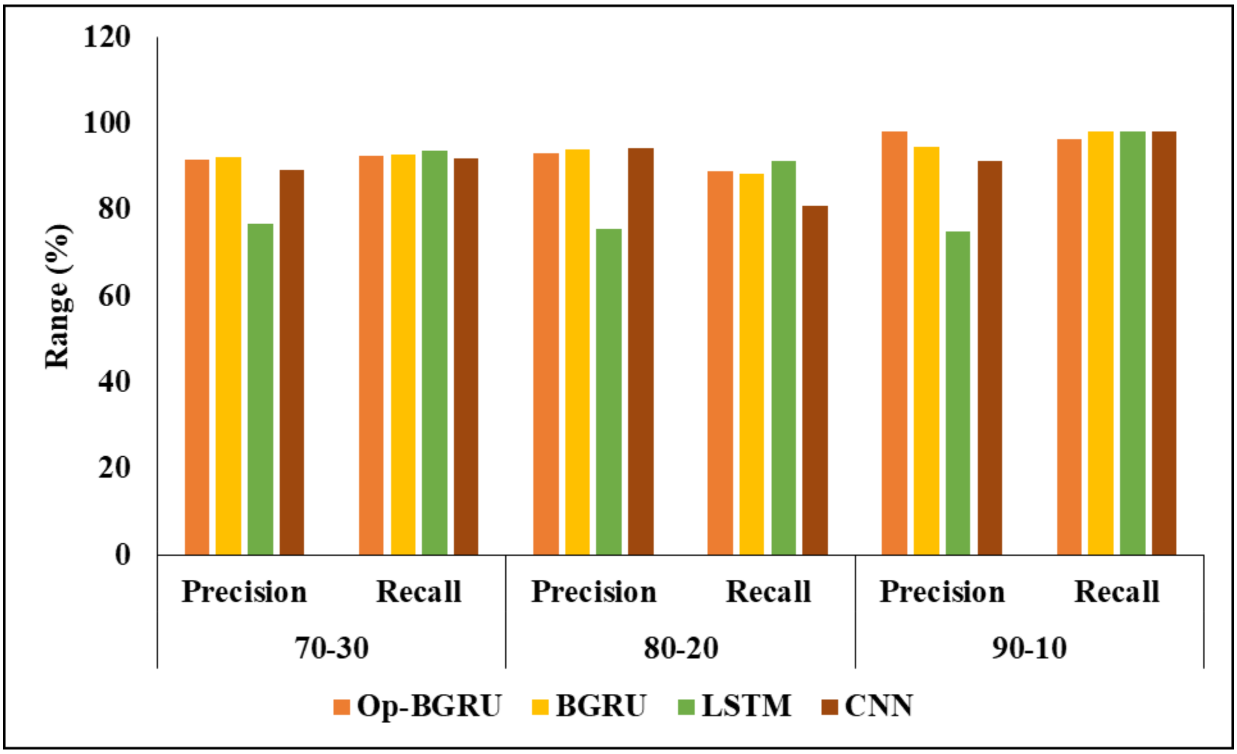

Figure 5: Validation Analysis of different models

5. Conclusions and Suggestions

Capital markets frequently have information asymmetry as a result of issues with agencies. This is especially true when it comes to declarations that showcase a company's operational performance, overall health, and potential for long-term growth. Unless the company goes bankrupt or experiences severe financial difficulties, few stakeholders, aside from a small group of shareholders directly involved in running the business, have a clear view of the company's financial situation. But occasionally, fraud involving financial statements does happen. For the benefit of certified public accountants and auditors, a reliable classical to recognize statement fraud must be developed. The current level of statement fraud detection literature is lacking, but using deep learning algorithms to address the limitations of traditional methods and embrace the age of big intelligence is the way to go. Thus, for feature selection, this study used an Op-BGRU in conjunction with MCHOA. To train and refine the model, To use data from 153 TWSE/TPEx listed businesses between 2001 and 2019. The confusion matrix, which F1-score, is several performance measures used in this work to validate the model and assess its generalizability and predictive power. Based on the results, the proposed model achieves a significantly higher accuracy (the most commonly used performance parameter) at 97.88%. Thus, our study adds to the existing literature and informs capital market practices concerning the avoidance of fraud.

The following suggestions for further study are made by this study: Incorporate growth or recession indicators macroeconomic factors as study variables to start. The second piece of advice is to look at applying supplementary econometric models like QARDL-ECM to deal with certain forms of financial and economic asymmetry and market-to-market asymmetry.

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