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Hybridized Gradient Lstm And Rnn For Ai-Iot Assisted Financial Disaster Prediction In Fintech Environment

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ABSTRACT

FinTech is a separate terminology that analyzes the financial technology industries inside a wider series of commands for firms using IT tools. As the Internet of Things (IoT) grows exponentially, AI-enabled flexible IoT is the future of financing. IoT's depth has likely changed the financial industry today, and it could quickly become a dominant instrument in the future. The use of AI and IoT can greatly enhance financial data extraction and customer support. Financial disaster prediction (FDP) seems to be a process of assessing a corporation's economic position. The Fintech index's forecast could also allow shareholders to prevent costs and help financial managements. So, we propose a novel hybridized gradient long short-term memory and recurrent neural network (HG-LSTM-RNN) in a FinTech setting. The financial information of global businesses is acquired in the beginning phase using IoT applications like mobile phones and computers. To select the optimum features, we utilize the flexible chaotic henry gas solubility optimization (FCHGSO) approach. Furthermore, the proposed approach is used to classify the gathered financial data with the greatest prediction rate. The performances of the proposed approach like sensitivity, F-score, accuracy are examined and compared with existing approaches to prove our research with the greatest effectiveness. The findings of those performances are depicted in graphical representation using the MATLAB tool.

Keywords: Fintech, Global Business, Financial industry, Economy, Artificial Intelligence (AI), Long Short-Term Memory (LSTM), Recurrent Neural Network (RNN), Flexible Chaotic Henry Gas Solubility Optimization (FCHGSO), MATLAB tool

1 Introduction

Since the 1990s, various financial crises were arisen regularly, wreaking havoc upon several nations' sectors of the business economy and transition [1]. This business economic collapse all had a contagion effect, i.e., they travel rapidly from the erupting nations to several other nations but have a huge variety of implications, rapid contagion, and significant implications [2, 3]. For instance, the current financial disaster that originated in the United States became more spreading to the rest of the globe in a short amount of time, wreaking havoc on worldwide financial, transition, and stock markets. As a consequence, many well-established financial institutions were shuttered, currency values in several nations plummeted, and stock markets plummeted. However, several nations experienced the business economic downturn.

FinTech is a phrase that relates to the use of digital technology to create financial products and services. FinTech has become widely regarded as a hotly debated blend of financial services and information technology [4-6]. However, the relationship between technology and the business economy seems to have a longstanding experience. FinTech is indeed a common term for a type of business making use of technological breakthroughs and transition economy features. It also tackles the legal and security issues that arise when new products and services are offered. Figure-1 depicts Fintech's impacts on the banking sector.

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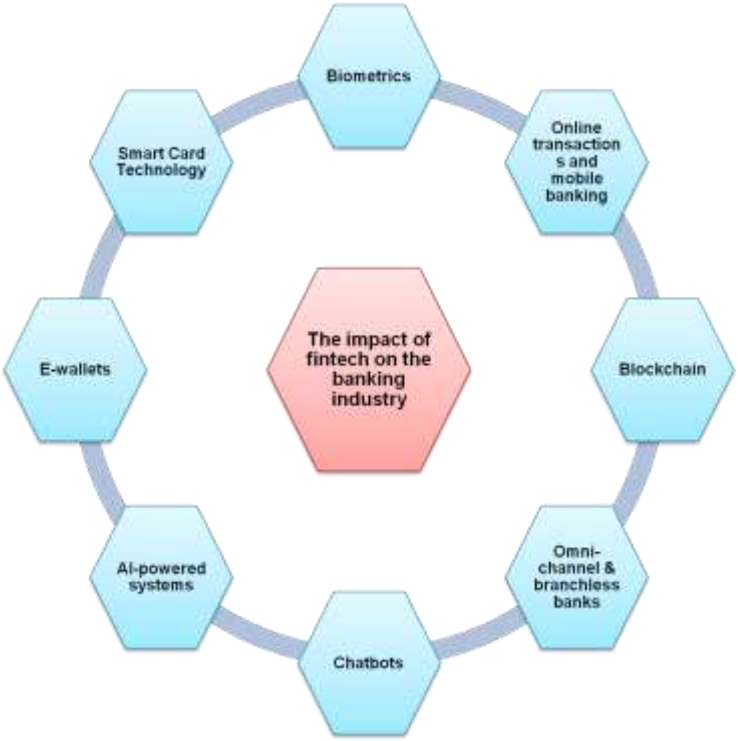

Figure 1: Fintech's impacts on the banking sector

FinTech advancement has created competitive pressure with traditional economic organizations. Many global businesses are competing for improvements to their current industry elements or new investment avenues to stay in the global business [7-9]. In practice, firms can detect potential hazards by examining and managing the business economic data regularly. The FDP is primarily important in the global business risk mitigation since it assists organizations in preventing and dispersing financial burdens in an accurate and timely manner.

It should be highlighted that almost all financial institutions regard FinTech as their primary investment. IoT could be included in the FDP system to collect the business's accounting information and execute timely market research. FDP is crucial for several financial bisinesses because it helps to reduce future economic losses by estimating the likely threat and avoids additional credit deals if such default risk reaches the highest adoption rate [10, 11]. This technique is known as the credit default classification subsystem, which identifies whether a customer is "non-default" or "default" if someone pays back a credit. The accuracy of FDP is an important factor in determining the financial business's effectiveness and output. For example, a slight increase in the accuracy level of a potential customer through default credit may reduce a business's future liability. FDP is viewed as an issue of the prediction process.

AI approaches [12] have recently been used to improve classical categorization techniques. Several difficulties, like overfitting, decreased compatibility, and increased processing cost, are caused by the existence of numerous elements in higher dimension financial data. This happens as a consequence of the dimensional nuisance on the sample-to-feature-count relation. This article presents a novel AI-IoT-assisted FDP using the hybridized gradient long short-term memory and recurrent neural network (HG-LSTM-RNN) in the FinTech setting. Here, the financial datasets are collected through IoT devices and are pre-processed by employing the normalization technique. To select the optimum features, we utilize the FCHGSO approach. Furthermore, the proposed approach is used to classify the gathered financial data with the greatest prediction rate. The additional detail of this work was organized as: topic II-Literature survey and problem statement; topic III-proposed work; topic IV-performance analysis; topic V-conclusion.

2 Literature Survey

Several investigation trials have lately been conducted to solve FDP concerns. [13] Regarding FDP, this study established an ideal FS employing elephant herd optimization (EHO) and a modified water wave optimization-based deep belief network (MWWO-DBN). The information has been normalized via 2 steps: formatting translation & data conversion. Then the precompiled data flow through EHO FS. The effective DBN-based classification is then used to categorize the information. The MWWO approach also enhances the

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effectiveness of the DBN framework. [14] They contain details of leakage & spread through stocks listed, sovereign bonds, including credit default swaps (CDSs) within a financial framework developed via linkages. They also develop machine learning to anticipate & assess spreading probability within a system of stocks, assets, and CDS. They utilize weekly information releases to calculate the interconnectedness rate. They employ significant stock indices, 10-year bond yields, and 5-year CDS. [15] This work employed a machine learning technique to study financial crisis facts. To adapt, XGboost, a novel technique, has been used. The outcome demonstrated that such approaches had a decent match & good efficiency, providing a new mechanism of FDP. Numerous modifications must be made. The information lacks characteristics. Furthermore, the financial crisis seems to be a global notion, thus focusing on people is inappropriate. Textual information analysis plus public opinion analysis can detect fear or overconfidence. [16] Google Trends statistics were added as independent factors to the time-varying dependent model to forecast the spreading impact. After that, Akaike information criterion (AIC) scores have been used to select the optimum match for every combination. [19] The impact of the 2008 crisis on leader behavior seems to be a major subject of management and leadership inquiry. Using the threat-rigidity assumption, they discovered how a direct threat affects leader behavior. Such findings expand leadership research by demonstrating the importance of the environment at diverse scales and, more crucially, how the environment as an antecedent impacts leadership action. This provides an additional field of leadership studies in which the environment is examined as an antecedent of leadership conduct as well as causal inference is possible. [20] They investigated the use of dissimilarity depiction to distinguish between bankruptcy vs non-bankrupt businesses. Thus, several well-known linear prediction methods are applied on both characteristic & disparity fields but also evaluated on a Korean private bank's dataset. Additional modeling investigations comparing linear & non-linear forecasting models on both disparity & characteristic fields will be useful for the future. [21] They created an innovative technology named Extreme Learning Machine (ELM) using oversampling (SMOTE). That method overcomes the limitations of parametric methods, which have been quickly violated if using financial ratio analysis as well as cumulative bank deposits for feed. It also eliminates the fundamental difficulties of finding the best ANN conceptual model & training necessary to calculate the neural network weight, then eventually solves the issue's mismatch. The technique also takes into account non-correlated factors. [22] They present a unique enhancement strategy to financial time-series prediction that avoids creating artificial time-series to enhance existing training examples. Every 200 epochs, ModAugNet-c chooses several of the pairs comprising ten organizations, selecting “five” at a moment, and feeds all into the Preventive Unit, whereas stock index information is correctly sent into the predictive unit. [23] In the topic of business bankruptcy forecasting, algorithms mainly tended to concentrate on particular nations or sectors, with little research taking a global view. This research examined bankrupt businesses from three areas over three years to see if there is a global trend that could describe the bankruptcy proceedings. [24] This research used the fruit fly optimization algorithm (FOA) to change the values of the factors throughout the ZSCORE financial crisis alert system. To achieve a better performance of the ZSCORE system, they use a GRNN prototype to anticipate the disparity between predict as well as the true value of such target attribute. Because the GRNN prototype selects a spread range at arbitrary, they have used the FOA to determine an optimum spread rate. For businesses in a certain stock market at a particular period, they suggested using the Multivariate Adaptive Regression Splines (MARS) technique to discover the optimal parameters in financial forecasting.

Problem statement

According to the preceding remarks, current international and domestic financial collapse protocols used numerical algorithms to correlate the success of multiple forecasting skills using mathematical calculations. Based on prior results, researchers indicate that the numerical approach's performance remains inconsistent, making linear value forecasting and nonlinear numerical pattern forecasting uncertain.

3 Proposed Work

As seen, IoT applications including mobile phones and computers are used to collect financial information about customers. Pre-processing involves the financial data translation, class labeling, and standardization. The ideal collection of characteristics is then retrieved via FCHGSO, whereas classification is done by using the HG-LSTM-RNN method. The presented model's process is fully discussed in the subsequent parts. The functional flow of this research is displayed in figure 2.

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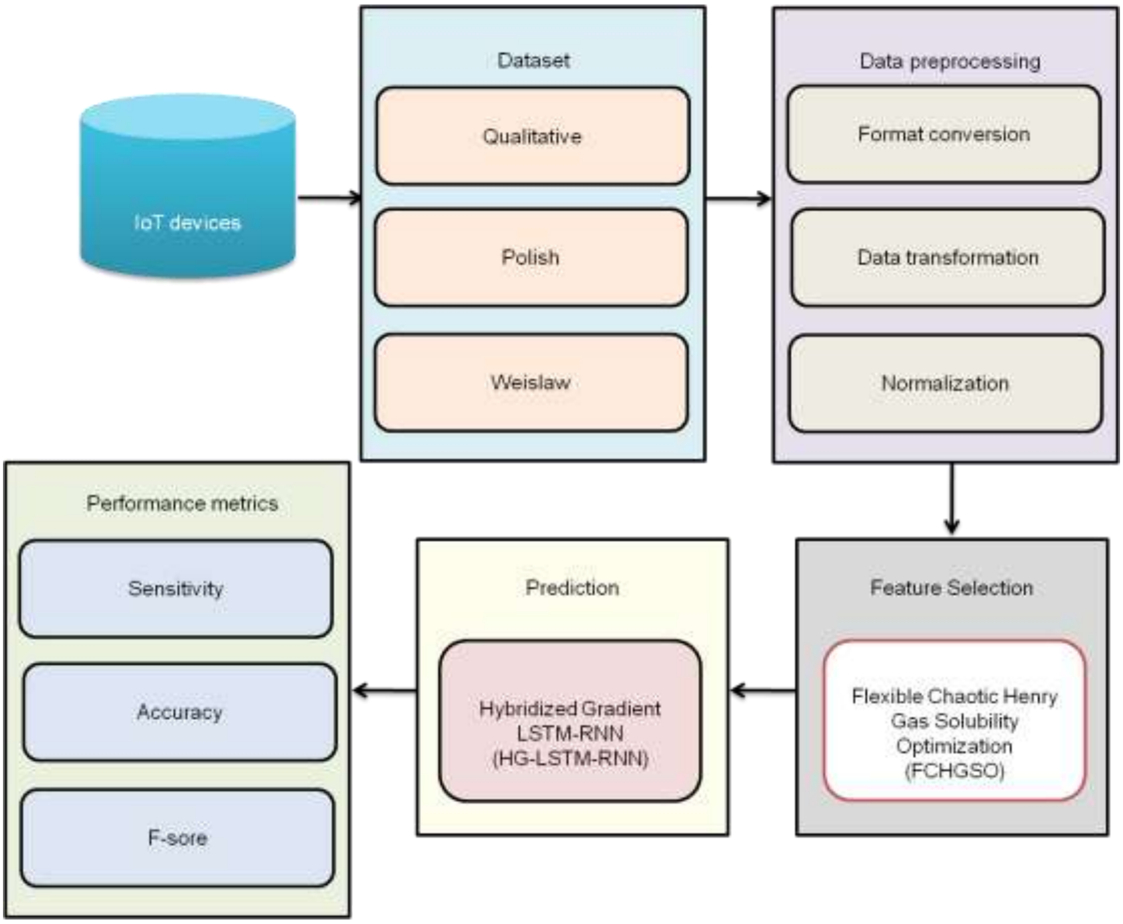

Figure 2: Functional flow of proposed research

Dataset

For this research, certain financial datasets like qualitative, polish, and weislaw are gathered from various resources such as UCI and Pietruszkiewicz. These datasets contain resources, cases, features, groups, FD/Non-FD categories. Table 1 depicts the dataset description regarding FinTech.

This dataset is available at https://link.springer.com/article/10.1007/s10479-021-04311-w [25].

The dataset's specifications are listed in Table 1. There are 251 samples inside the qualitative collection, each with seven characteristics. A total of 43,406 samples containing 65 characteristics are included in the Polish collection. The Weislaw collection, similarly, contains 242 samples with 31 characteristics.

Table-1: Financial datasets description

Financial Datasets	Resources	Cases	Features	Groups	Failed/Non-Failed
Qualitative	UCI	251	7	2	107/141
Polish	UCI	43406	65	2	2091/41312
Weislaw	Pietruszkiewicz	242	31	2	112/126

Data pre-processing

The target data should be chosen from the raw collection of financial data to boost performance. After obtaining the target data, preparation is required to create it usable. The following phase uses the fully prepared information to analyze it and generate information or results using data mining methods. Data transformation is used to change the pattern and the characteristic type. For instance, if the financial information is in numeric form yet the database needs float.

Data pre-processing is an essential process of data extraction and processing. Collected financial data is typically unstructured, leading in values outside the range. Lack of quality control in data analysis might cause inaccurate outcomes. So, before performing an investigation, make sure the data is represented correctly.

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Information retrieval is more challenging when there are a lot of duplicates or ambiguous information. So, we employ the normalization approach to get the data without uncertain patterns. The collected dataset must be purified and normalized to delete repeated and redundant noises, along with data that is inadequate. Since the records for business are so large, sample compaction techniques must be employed. Because this dataset has several features, image retrieval methods are needed to sort out the ones which aren't significant. The dataset may be normalized during the pre-processing stage.

Equation (1) defines the c-count in mathematical form as,

$$\mathrm{C} = [(\mathrm{M} - \beta\,)/\tau] \tag{1}$$

Here, β=mean of the information, and τ=standard deviation. And C is represented as,

$$\mathrm{C} = \frac{\mathrm{M}-\bar{\mathrm{M}}}{\mathrm{Sd}} \tag{2}$$

Here $\bar{M}$=mean of the specimen, and Sd=standard deviation of the specimens.
The random specimen looks like this:

$$C_k = \delta_0 + \delta_1 M_r + \rho_r \tag{3}$$

The defects that are depending on τ^2 are represented by r.
Ensuring that, as seen below, the defects should not depend on one another.

$$t_m \sim \sqrt{U}\,\frac{t}{\sqrt{t^2+u-1}} \tag{4}$$

Here, t=random parameter.

After that, the standard deviation is used to standardize the variable's moves. The momentary scale deviation is calculated using the formula (5).

$$\mathrm{MMS} = \frac{\mu^{\mathrm{mms}}}{\theta^{\mathrm{mms}}}$$

(5)

Here, momentary scale is denoted by mms.

$$\mu^{\mathrm{mms}} = \mathrm{Ex}(\mathrm{M} - \beta)\text{^}\mathrm{MMS}$$

(6)

Here, M=random variable, and Ex=predicted values.

$$\theta^{\mathrm{mms}} = \left(\sqrt{Ex(M - \beta)\text{^}MMS}\right)\text{^}2 \tag{7}$$

$$t_u = \frac{mms}{\bar{M}}$$

(8)

Here, t_u= coefficient of variance.

The characteristic scaling procedure will be stopped by setting all of the parameters to 0 or 1. The unison-based normalizing approach is the name for this procedure. The normalized formula would look like this:

$$M' = \frac{(t-t_{min})}{(t_{max}-t_{min})} \tag{9}$$

The finalized financial information should be considered valid & acceptable for more analysis following consistent chaining of data preparation procedures.

Features selection using Flexible Chaotic Henry Gas Solubility Optimization (FCHGSO)

The raw finance information obtained by IoT systems inside a Fintech context is used to generate an appropriate range of attributes during the feature selection process. According to Henry's rule, the largest amount of solute that might dissolve in a given amount of solvent at a given pressure/temperature is referred to as solubility. As a result of Henry's rule's behavior, the HGSO has been encouraged. It's used to figure out how well low-solubility gases dissolve into liquids. Moreover, solubility is influenced by heat and pressure; under elevated temperatures, solids are becoming more soluble, whereas gases are less soluble. When it came to pressure, the solubility in gas grew as the pressure was raised. Below is a quantitative definition.

Stage-1: Process for starting. Equation (10) was used to calculate the size of the population N as well as the position of the gas:

ISSN:2336-2693 | E-ISSN:2336-4890
ISSN:2658-0845 | E-ISSN:2658-2430

$$Z_i(t+1) = Z_{min} + r \times (Z_{max} - Z_{min}) \tag{10}$$

Here, r=number between 0 and 1, Z_{max}=maximum boundary value, Z_{min}=minimum boundary value, and t=duration of iteration.

Equation (11) determines the quantity of gas i, Henry constant of type j($H_j(t)$), partial pressure $P_{i,j}$ of gas i inside the group j, and ∇_{sol} E/R constant value of type j (C_j):

$$H_j(t) = y_1 \times rand(0,1), P_{i,j} = y_2 \times rand(0,1), C_j = y_3 \times rand(0,1) \tag{11}$$

Here, y_1, y_2, and y_3 denote constant values.

Stage-2: The population component gets divided into equal groups based on the number of gas types present. The gas & Henry's constant values are the same as any other group (H_j).

Stage-3: Each group j was computed to find the best gas. After that, the gas is assessed to find the best gas for the entire swarm.

Stage-4: The Henry parameter should be increased. It must be updated based on equation (12) as follows:

$$H_j(t+1) = H_j(t) \times \exp\left(-C_j \times \left({}^{1}/_{T(t)} - {}^{1}/_{T^\theta}\right)\right), T(t) = \exp\left(-{}^{t}/_{iter}\right) \tag{12}$$

Here, H_j=Henry's factor for group j, T=temperature, T^0=constant and T^0=298.15, and iter=total number of rounds.

Stage-5: Enhance solubility. It must be improved based on equation (13) that follows:

$$S_{i,j}(t) = K \times H_j(t+1) \times P_{i,j}(t) \tag{13}$$

Here, $S_{i,j}$=gas's solubility of the group j and K=constant.

Stage-6: Boost the position, and we can do it in the following ways:

$$Z_{i,j}(t+1) = Z_{i,j}(t) + F \times r \times \gamma \times \left(Z_{i,best}(t) - Z_{i,j}(t)\right) + F \times r \times \alpha \times \left(S_{i,j}(t) \times Z_{best}(t) - Z_{i,j}(t)\right)$$
$$\gamma = \beta \times exp\left(-\frac{F_{best}(t)+\varepsilon}{F_{i,j}(t)+\varepsilon}\right), \epsilon = 0.05 \tag{14}$$

Here, $Z_{i,best}$=optimum gas i within group j, Z_{best}=swarm's optimum gas, γ=capability of gas j in group i to interact with gas in its group, α=effect of another gas in group j over gas i and is equal to 1, β=constant, $F_{i,j}$=fitness of gas i in group j, and F_{best}=fitness of optimum gas in the overall framework.

Z_{best} signifies two factors in responsible of balancing exploitation as well as exploration capabilities, and F=flag that affects the path of the search agent as well as provides diversity=±.$Z_{(i,best)}$.

Stage-7: Get away from the local optimal. It's used to get away from the local optimum. Choose and rate the number of a worst agent using the algorithm below:

$$N_w = N \times (rand(C_1 - C_2) + C1), C_1 = 0.1 \; and \; C_2 = 0.2 \tag{15}$$

Here, N=number of search agents.

ISSN:2336-2693 | E-ISSN:2336-4890
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Stage-8: Modify the worst agent's position.

$$G_{(i,j)} = G_{\min(i,j)} + r \times \left(G_{\max(i,j)} - G_{\min(i,j)}\right) \tag{16}$$

Here, G_{min} and G_{max} denote boundaries.

HGSO includes both exploitation & exploration phases, making it a global optimal approach. Furthermore, the number of operators that need to be changed in HGSO has been lowered, making the approach comprehensible and execute.

As a result, the total complexity, which includes the objective function (obj) defined with equation (14) and calculated using $X(t.n.d) * X(obj)$.

Here, t=maximum number of iterations, n=number of solutions, and d=number of parameters.
The chaotic concept is incorporated as well as developed from the FCHGSO technique to enhance the HGSO method's convergence speed.

Chaos seems to be an unsteady type of dynamic behavior that seems to be particularly vulnerable to basic circumstances. For eliminating traps inside the local optimum & expanding the number of possibilities, chaos is used in numerous optimization approaches. Exploitation & exploration are the two principles that guide each meta-heuristic approach. Exploitation advances the search for ideal solutions, whereas exploration allows for the most effective search. The chaos was presented as meta-heuristic frameworks for achieving a good response by establishing a balance between exploration and exploitation.

The chaos is added to acquire improved resources throughout exploration and exploitation during all search regions, hence improving the efficacy of the proposed approach in identifying the appropriate global solution. The chaotic map is used to determine the position z_i^k in which the variable 'θ' is substituted with the value, obtained using the chaotic map and equation (17):

$$z_i^{k+1} = z_i^k + C_{map} \times \left(z_{BH} - z_i^k\right), i = 1,2 \dots N_{\nabla} \tag{17}$$

Here, z_i^k=location of i^{th} star at k^{th} iteration, z_i^{k+1}=location of ith at $(k+1)^{th}$ iteration, z_{BH}=BH's position in space/field, C_{map}=chaotic map, and N_s=amount of stars.

The values of random variables from the HGSO approach are then adjusted using chaotic maps. The FCHSGO approach has been used to FS by using the wrapper method to select the best characteristics. People with the optimum feature subsets lower the specific characteristics while improving prediction performance, depending upon the fitness function (FF). Initialization & updated solutions are the two phases of the FS procedure. The HGSO generates an initial population of N candidate solutions during the initial stage, with each person representing a subset of characteristics to be estimated. This step is crucial to the convergence & reliability of the best solutions. Equation (10) generates the population Z^0 at random.

In this work, the lower and upper bounds lb_i and ub_i of every candidate solution, i should in the range (0, 1). Before the fitness phase, a step known as the binary modification is forced to set a set of attributes. As a result, equation (18) must be used to convert the solutions z_i^0 into binary z_i^{bin}:

$$z_i^{bin} = \begin{cases} 1 \; if \; z_i^0 > 0.5 \\ 0 \; otherwise. \end{cases} \tag{18}$$

Consider the solution z_i comprises six components like z_i^0=[0.6, 0.1, 0.7, 0.43, 0.2, 0.81] to show the transformation technique.

For creating a binary vector, equation (19) performs the method of transition: z_i^{bin}=[1, 0, 1, 0, 0, 1], where "1" denotes a characteristic to be selected; otherwise, "0" denotes unchosen. It states that in real databases, the first, third, and last characteristics are acceptable and must be selected; when some other characteristic is unsuitable, it

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must be omitted. After establishing the subgroup of desirable characteristics, FF is applied to each solution z_i^{bin} to determine the characteristic's goodness. Equation (19) determines the objective value of the i^th^ solution.

$$Fit_i = w_1 \times Er_i + w_2 \times \frac{d_i}{D} \tag{19}$$

Here, w_1=0.99, w_2=1-w_1, and D=total size of the characteristics in the original dataset.

Equalization component w_1 reflects the amount of selected characteristics d_i that is used to maintain equilibrium among Er_i (classification error rate). The error rate of the test dataset analyzed using the HG-LSTM-RNN framework is denoted by Er_i. The HG-LSTM-RNN framework includes the test set to assess the effectiveness. Table 2 shows the results of the FCHGSO framework.

Table-2: Outcome of FCHGSO approach

	Qualitative	Polish	Weislaw
Best cost	0.06472	0.04352	0.04273
Selected features	2,3,5	4,5,6,9,10,12,13,14,17,19,22,24,26,28,29,32,24,27,35,38,40,46,48,50,54	2,3,4,5,8,9,11,13,15,18,22,25

Prediction using Hybridized Gradient Long Short-Term Memory and Recurrent Neural Network (HG-LSTM-RNN)

The HG-LSTM-RNN method is used to establish the appropriate class labels for the applicable financial records after the feature selection subset is formed. This approach can fit in all states for the greatest forecasting and the framework of this approach is depicted in figure 3. RNN is a DL (deep learning) structure, which succeeds in analyzing time series data due to its internal state's ability to reflect dynamic temporal properties. Nevertheless, when the data interval (the specified fixed length) grows longer, the probability of gradient fading develops, which would be produced by the weight matrix and the reciprocal of the tanh (from 0 to 1) function being multiplied successively. As an expanded variation of RNN, LSTM has the potential to successfully ameliorate the phenomena of gradient fading in regular RNN. LSTM uses a gate control scheme to evaluate whether an input must be recalled or discarded, and it can make use of long-time sequence data to a certain level.

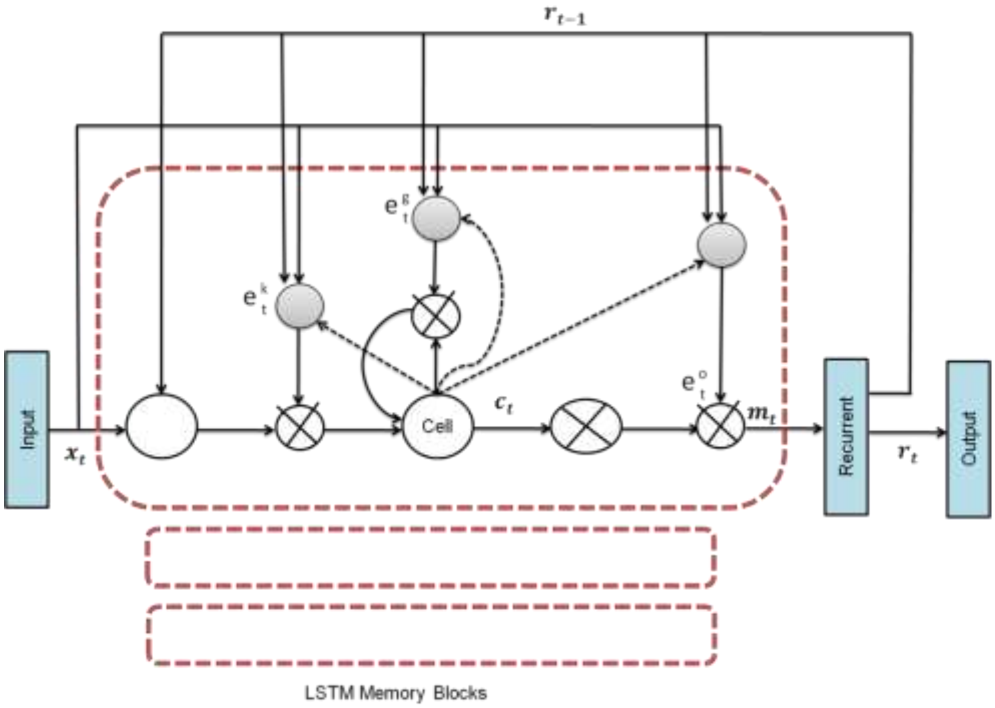

Figure 3: Framework of HG-LSTM-RNN

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LSTM substitutes RNN neurons by memory blocks including 3 kinds of gates (input, forget, and output gates). Equations (20-25) could be used to represent the data calculated inside LSTM memory blocks.

$$e_t^g = \sigma(B^g X_t + R^g h_{t-1} + \xi^g) \tag{20}$$
$$e_t^k = \sigma(B^k X_t + R^k h_{t-1} + \xi^k) \tag{21}$$
$$m_t^c = \tanh(B^m X_t + R^m h_{t-1} + \xi^m) \tag{22}$$
$$c_t = e_t^g * c_{t-1} + e_t^k * m_t^c \tag{23}$$
$$e_t^o = \sigma(B^o X_t + R^o h_{t-1} + \xi^o) \tag{24}$$
$$c_t = e_t^o * \tanh(c_t) \tag{25}$$

Here, e_t^g=forget gate during the time (t), e_t^k=input gate during t, e_t^o=output gate during t, m_t^c=candidates of input to be stored at t, c_t=memory cells at t, h_t=hidden state at t, X_t=input vectors at t, ξ^g=bias vector of forget gate, ξ^k=bias vector of input gate, ξ^o=bias vector of output gate, and ξ^m=bias vector of candidates of the input. Then B^g, B^k, B^m, B^o, R^g, R^k, R^m, R^o are related weight matrices. The "Hadamard product" was indicated as $*$ among two matrices. Furthermore, σ and $\tanh$ were termed as activation functions.

HG-LSTM-RNN was used to categorize the financial position of the data in this research. For categorization, the HG-LSTM-RNN including LSTM hidden layer has been established. For all hidden layers, the quantities of hidden along with hidden units are chosen by trial-and-error. Five neurons make up the subsequent layers, which are used to categorize four different kinds of abnormalities and noisy regions. Due to the obvious LSTM-DL overhead, holdout cross-validation was used rather than k-fold cross-validation throughout the training stage. For the possibility of providing an HG-LSTM-RNN, the sampling dataset is divided into two sets: training & verification. As a result, the accuracy rate is limited, indicating, therefore, it is under-fitting. Whenever the number of hidden layers gets raised, the task is difficult.

A network that has the highest training accuracy but the lowest verification performance is said to be over-fitting. The LSTM processing time is set to 5 to obtain optimal functionality and training timekeeping. It is recommended that LSTM is fed 5 frames for inputs. As a result, the HG-LSTM-RNN approach is subjected to a huge period of training. The amount of time spent training has decreased.

Performance Analysis

The testable theories of the proposed approach are evaluated throughout this part, as well as the simulation procedure is carried out by using the MATLAB tool. The FCHGSO approach has provided the best FS outcomes across all data tested, as shown in the table 2. The FCHGSO approach performed well with the best costs of 0.06472, 0.04352, and 0.04273, correspondingly, for the [qualitative, polish, and weislaw] financial collections. For these same datasets, our proposed HG-LSTM-RNN approach is applied to accomplish the greatest finance disaster prediction. From this investigation, we gain certain metrics like accuracy, sensitivity, specificity, and f-score. These metrics are assessed through the below-mentioned calculations and specify the efficacy of the proposed technique.

Accuracy (Ac)

Accuracy provides the categorization with the required financial s. Figure 4 depicts the comparison of accuracy with proposed and existing techniques regarding the specified financial collections. In this graph, the x-axis denotes financial datasets and the y-axis denotes accuracy. By employing equation (26), we accomplish the highest accuracy of our proposed approach over existing approaches.

$$Ac = \frac{(tp+tn)}{(tp+tn+fp+fn)} \tag{26}$$

Here, true positive=tp=amount of right forecasts of a positive sample, true negative=tn=amount of right forecasts of a negative sample, false positive=fp=amount of wrong forecasts of a positive sample, and false negative=fn=amount of wrong forecasts of a negative sample.

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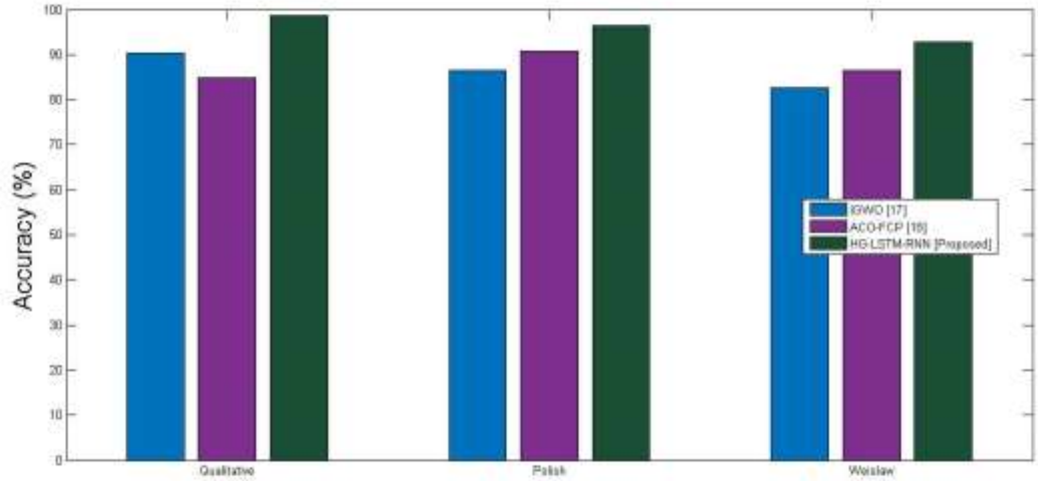

Figure 4: Comparison of accuracy with proposed and existing techniques

Specificity (spe)

The effectiveness of a method to forecast the true negatives of every specified financial type is measured by its specificity. Figure 5 depicts the comparison of specificity with proposed and existing techniques regarding the specified financial collections. In this graph, the x-axis denotes financial datasets and the y-axis denotes specificity. By employing equation (27), we accomplish the highest specificity of our proposed approach over existing approaches.

$$spe = \frac{tn}{tn+fp} \tag{27}$$

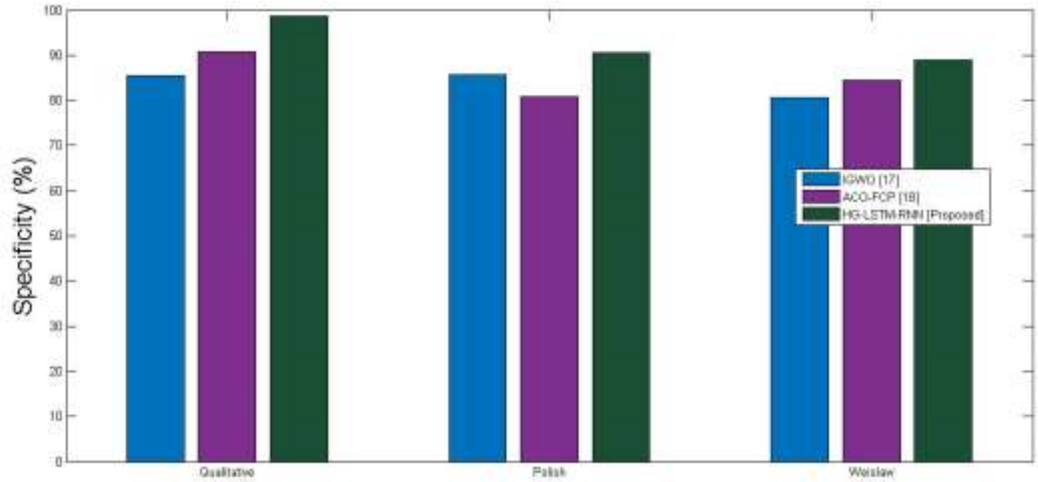

Figure 5: Comparison of specificity with proposed and existing techniques

Sensitivity (sen)

The statistic that measures a model's potential to anticipate a true positive in every specified financial type is called sensitivity. Figure 6 depicts the comparison of sensitivity with proposed and existing techniques regarding the specified financial collections. In this graph, the x-axis denotes financial datasets and the y-axis denotes sensitivity. By employing equation (28), we accomplish the highest sensitivity of our proposed approach over existing approaches.

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$$sen = \frac{tp}{tp+fn} \tag{28}$$

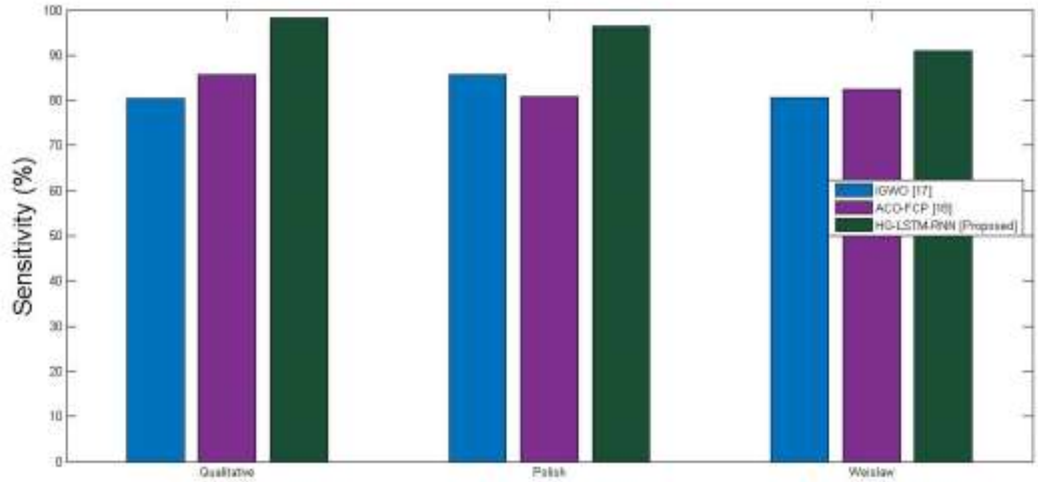

Figure 6: Comparison of sensitivity with proposed and existing techniques

F-score

The F-score is a metric for determining how accurate a prediction is on a given financial data. Figure 7 depicts the comparison of f-score with proposed and existing techniques regarding the specified financial collections. In this graph, the x-axis denotes financial datasets and the y-axis denotes f-score. By employing equation (29), we accomplish the highest f-score of our proposed approach over existing approaches.

$$F - score = \frac{tp}{tp+0.5\,(fp+fn)} \tag{29}$$

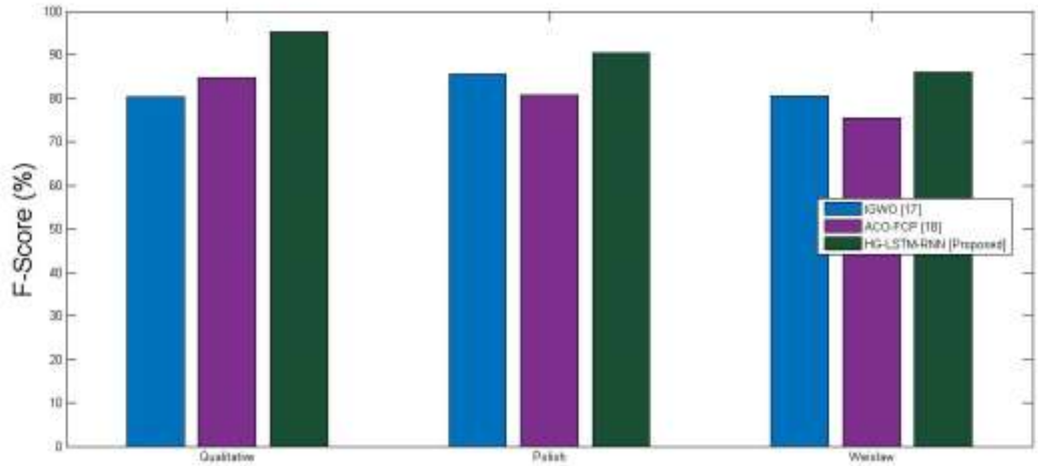

Figure 7: Comparison of f-score with proposed and existing techniques

In this part, the investigation analysis was demonstrated regarding FDP. From this assessment, we accomplished the proposed approach with the greatest level of financial disaster prediction than the existing approaches.

4 Conclusion

In the IoT context, this research has developed an effective prediction method for describing the financial disaster of the firm. The proposed research first allows IoT devices such as mobile phones, computers, and other

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devices to collect financial information about the user, which is then uploaded to a remote server. On the server-side, FDP occurs at three stages: data pre-processing, the FCHGSO feature selection technique, and the HG-LSTM-RNN based classification framework. The FCHGSO approach aids in the removal of undesirable characteristics, resulting in a significant improvement in the prediction performance of the HG-LSTM-RNN framework. This proposed approach was compared with the existing approaches to prove our research with the greatest financial disaster prediction. As a part of the future scope, the framework of the extended work is based on federated learning and blockchain models that add on secured intelligence to the existing work and fast converging computing advancement for Fintech.

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