Jellyfish Search Algorithm Based Feature Selection with Optimal Deep Learning for Predicting Financial Crises in the Economy and Society

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Abstract

The financial crises has emphasized the part of financial relationship as a potential source of macroeconomic variability and systemic risk worldwide. Predicting financial crises using deep learning (DL) infers leveraging neural network (NN) to identify patterns indicative of future financial crisis and analyse complicated financial data. DL approaches such as recurrent neural network (RNN) or long short-term memory (LSTM) that process a massive quantity of past financial data such as geopolitical events, economic indicators, and market prices. These models target to identify refined connections and signals that can lead to an economic recession by learning from earlier crisis and their precursors. The problem resides in the complex and dynamic nature of financial market, demanding continuous training and modification of methods to retain significance in the aspect of developing financial condition. Although DL shows the potential to increase prediction capabilities, it's vital to accept the inherent ambiguity in financial market and the requirement for cutting-edge development of models to enhance their accuracy and reliability. This study proposes a jellyfish search algorithm based feature selection with optimum deep learning algorithm (JSAFS-ODL) for financial crisis prediction (FCP). The objective of JSAFS-ODL technique is classified the presence of financial crises or non-financial crises. To accomplish this, the JSAFS-ODL technique applies JSA based feature selection (JSA-FS) to choose an optimum set of features. Besides, RNN-GRU model can be used for the FCP. For enhancing the detection results of the RNN-GRU approach, chimp optimization algorithm (COA) can be utilized for the optimal tuning of the hyperparameters correlated to the RNN-GRU model. To guarantee the better performance of the JSAFS-ODL procedure, a series of tests were involved. The obtained values highlighted that the JSAFS-ODL technique reaches significant performance of the JSAFS-ODL technique.

Keywords: Financial Crisis; Artificial Intelligence; Chimp Optimization Algorithm; Feature Selection; Deep Learning

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1. Introduction

Financial crises are large economic and social expenses. Noticing their earlier warning indications is appropriately a higher priority for policymakers. Accordingly, it must decrease the severity and potentiality of financial crises regardless of increasing risks, and facilitated the earlier activation of counter-cyclical macro-prudential policies [1]. However, recognizing a consistent set of timely warning predictors is a challenge for numerous causes. Primarily, it is a comparatively smaller category of perceived crises that creates robust modeling complexity [2]. Secondarily, crisis indicators frequently flash red only once it can be already delayed to interfere. Next, it is challenging to refine difficult earlier warning systems into easy and apparent indicators, which could be supported to control earlier involvement by macroprudential authorities [3]. Lastly, financial and economic systems have been subjected to intrinsic unpredictability and 'Knightian' uncertainty in which any measures can be almost definitely unknown in advance, as the financial effect from Covid-19 represented, while recognizing essential vulnerabilities can be quite beneficial for these conditions [4].

Artificial intelligence (AI) techniques are machine-based model with differing levels of self-sufficiency, which can be in specified collection of human-defined objectives, make evaluations, decisions or recommendations [5]. AI technologies should progressively employing large quantity of another data sources as well as data analytics described to as 'big data' [6]. The data source machine learning (ML) methods implement this data for learning and increasing predictability as well as automatic performance utilizing data and involvement, devoid of existing programs carried out by humans. Nevertheless, the occurrence of diverse features in the higher-dimensional economic data provides numerous issues namely higher computational difficulty, low interoperability, and over-fitting [7].

This issue is reducing the accessible number of features with feature selection (FS) techniques for resolving the standard method. The FS algorithm is a major important and efficient pre-processing phase at Data Mining. This can be liable for extracting the undesirable as well as redundant features from original data [8]. In addition, this could be implemented to remove greater potential data over least feature subsets and potential features such as diminishing impure features, computational time, lower cost, and noise removal, which could be important for applying an approximation technique. Likewise, FS has been employed to process the subset of features on the applications of fixed value rather than by chosen features. The key difficulty in such a technique could be identified optimal features at accessible features named NP-hard issues [9]. Several algorithms should be implemented for recognizing limited solutions through short period intervals. Particular ML methods namely ant colony optimization (ACO), gray wolf optimizer (GWO), and particle swarm optimization (PSO) must be utilized in selecting important features, but, this techniques does not related to the commercial application, mostly in financial crises prediction (FCP) [10].

This manuscript presents a jellyfish search algorithm based FS with optimum DL model (JSAFS-ODL) for financial crises prediction (FCP). The purpose of the JSAFS-ODL approach is to classify the presence of financial crisis or non-financial crisis. To accomplish this, the JSAFS-ODL technique applies JSA based feature selection (JSA-FS) to chosen an optimum features. Besides, RNN-GRU model can be used for the FCP. To improve the detection results of the RNN-GRU model, chimp optimization algorithm (COA) can be utilized for the optimal tuning of the hyperparameters related to the RNN-GRU model. The obtained values highlighted that the JSAFS-ODL technique reaches significant performance of the JSAFS-ODL technique.

2. Literature survey

Katib et al. [11] introduced a hybrid hunter-prey optimizer included to DL-based FCP (HHPODL-FCP) model. This algorithm creates the utility of HHPO method for the FS algorithm. Moreover, HHPODL-FCP approach implements the gated attention recurrent network (GARN) architecture to identify and classify non-financial as well as economic crises. The HHPODL-FCP system employs a SSA-related hyperparameter alteration technique for increasing GARN framework. Yang [12] designed a model-enabled DL method for forecasting the financial indicator rates. This developed model utilizes the long short-term memory (LSTM) method similar to a standard forecast system. The financial indications contain price to sales ratio (PTSR), return on tangible assets (ROTA) of Mondelez International (MDZL), price-earnings ratio (PER), and Hormel Food Corp (HRL) stock businesses, confirming this developed model.

Venkateswarlu et al. [13] projected an ant lion optimizer aided FS by a ML-assisted detection (OALOFS-ML) technique. In big data management, the Hadoop MapReduce tool was utilized at the financial field. Moreover, this introduced OALOFS-MLC system develops an innovative OALOFS method for choosing better features that support to obtain increased classification outcomes. Further, the deep random vector functional links network

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(DRVFLN) framework could be implemented in the execution of categorizing tasks. Yan and Aasma [14] designed a new DL hybrid prediction approach for stock markets such as CEEMD-PCA-LSTM. In this method, complementary ensemble empirical mode decomposition (CEEMD) was employed for decomposing the trends or variabilities. Next, PCA decreases dimension of the decomposed IMFs module. Subsequently, higher-level intellectual features have been individually provided into LSTM models. Lastly, the prediction measures of separate modules could be implemented for achieving the ultimate predicted values.

Chen and Long [15] implemented factor analysis (FA) for acquiring the prevalent features among the novel non-financial and financial signs. Initially, mean square error (MSE) of an output as well as projected values of the LSTM was utilized as the FF of intelligent swarm optimizer method, followed by the PSO algorithm can be exploited for optimization. Lastly, a financial risk forecasting method depends upon FA-PSO-LSTM DL was established, and numerous benchmark techniques have been presented. Fan et al. [16] employed the quantity of Internet search and evaluated the connection among Taiwan Weighted Stock Index and search volume. The search volume offered by Google Trend that could be implemented for unit root and correlation analyses. Afterwards, these acquired keywords were examined in a 2 experiments namely ML, and search trend. A NN must be chosen for comparison with the search trends in another test.

Ayvaz et al. [17] aimed to reduce the shortage in the planned rate organization and FCP. Sustainable Balanced Scorecard (SBSC) has been introduced as a strategic rate controlling tool was created at an active manner by incorporating the earlier warning model designed for companies with a new method as SBSC. Also, an earlier warning system was devised with LSTM networks by employing financial macro variables in micro domain. Uthayakumar et al. [18] projected a group based detection technique comprises a 2 models such as enriched K-means clustering and fitness-scaling chaotic genetic-ACA (FS-CGACA) enabled classification method. In the primary phase, an enriched K-means technique was presented for removing the incorrect cluster information. Subsequently, a rule-based system was preferred for correct the specified database. Finally, FSCGACA was implemented for searching the optimum parameters of the rule-based method.

3. The Proposed Method

In this study, we have presented an innovative JSAFS-ODL system for FCP. The purpose of the JSAFS-ODL method is to classify the presence of financial crises or non-financial crises. To accomplish this, the JSAFS-ODL algorithm encompasses a 3 main procedures like JSA based FS, RNN-GRU based classification, and COA based parameter tuning.

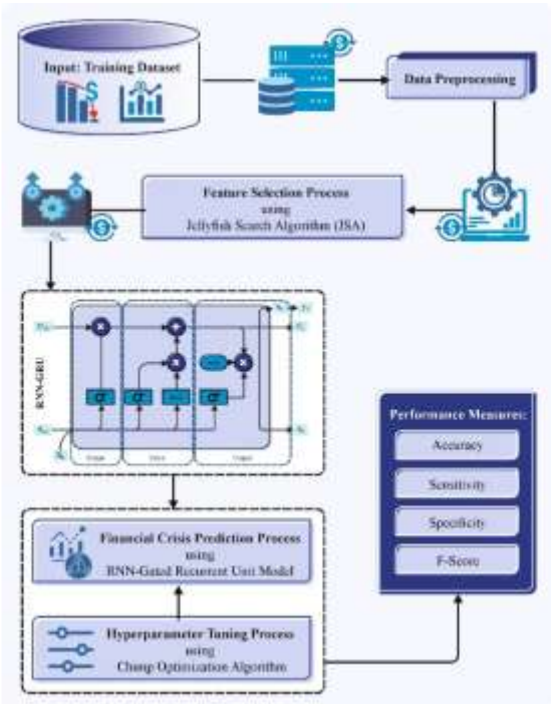

Figure 1: Process involved in JSAFS-ODL Model

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A. JSA based Feature Selection

At this primary stage, the JSAFS-ODL technique applies JSA-FS to elect an optimal set of features. The JSA is enthused by an optimum technique of the jellyfish (JF) action and foraging behavior in the sea [19]. The movement behavior of JF is chiefly impacted by the track of ocean current, JF swarm as well as time control mechanism (TCM):

Ocean current: It is highly rich in nutrients that generates simple for JF. The ocean present direction, $\overrightarrow{trend}$ indicates the average vector among the location X of entire JF and the current optimum location of the JF, X^*. The way of ocean current and position upgrade of the i^{th} JF moving with an ocean current is correspondingly conveyed below:

$$\overrightarrow{trend} = X^* - \beta \times rand(0,1) \times \mu \quad (1)$$

$$X_i(t+1) = X_i(t) + rand(0,1) \times \overrightarrow{trend} \quad (2)$$

Whereas, β refers to the allocation coefficient, μ denotes the average vector among whole JF and one with an optimal solution, rand $(0\ and\ 1)$ has an arbitrary count in an interval of $[0\ and\ 1]$, and t refers to the time identified as the number of rounds.

JF swarm: There are dual kinds of JF swarm actions such as passive motion (type A) as well as active movement (type B). When a JF swarm primary forms, most JF discover by passive movement. But, many JF are screening active movement for exploration. Type A movement swarms transfer by rotating near their specific location, and the consistent location upgrade of every JF is represented as follows

$$X_i(t+1) = X_i(t) + \gamma \times rand(0,1) \times (U_b - L_b) \quad (3)$$

Whereas L_b signifies the lower bound, U_b denotes the upper bounds of search space; $\gamma > 0$ means motion constant which is associated to an array of sign round the JF location. In addition, in type B movement, a JF i, alternatively the current JF i, is arbitrarily nominated, and the vector from JF i to the designated JF j is employed to define the movement way. When the food amount (or FV) of the particular JF j's place beats the current JF i's place, the final will travel near the transfer away. Therefore, every JF travels in an enhanced way to discover additional food, and this method of movement can be measured as extremely effective in local search. The movement of active way is conveyed as

$$X_i(t+1) = X_i(t) + \overrightarrow{step} \quad (4)$$

Where

$$\overrightarrow{step} = rand(0,1) \times \overrightarrow{dir} \quad (5)$$

And

$$\overrightarrow{dir} = \begin{cases} X_j(t) - X_i(t), if\ f(X_i) \geq f(X_j) \\ X_i(t) - X_j(t), otherwise \end{cases} \quad (6)$$

Whereas $f(\cdot)$ denotes the objective function at the place X.

TCM: It manages the ratio among the JF movement subsequent the ocean current and JF swarm. This contains of constant C_o (set to 0.5) and time control function $c(t)$. The $c(t)$ is an arbitrary value that alters among (0,1) and it is expressed by

$$c(t) = \left| \left(1 - \frac{iter}{iter_{\max}}\right) \times (2 \times rand(0,1) - 1) \right| \quad (7)$$

If $c(t) \geq C_0$, the JF movement direction of the ocean current; if $c(t) < C_0$, the JF moves within the JF swarm. If rand $(0,1) > (1 - c(t))$, the JF discovers with inactive movement; or else with active movement. Fig. 2 depicts the process involved in JSA.

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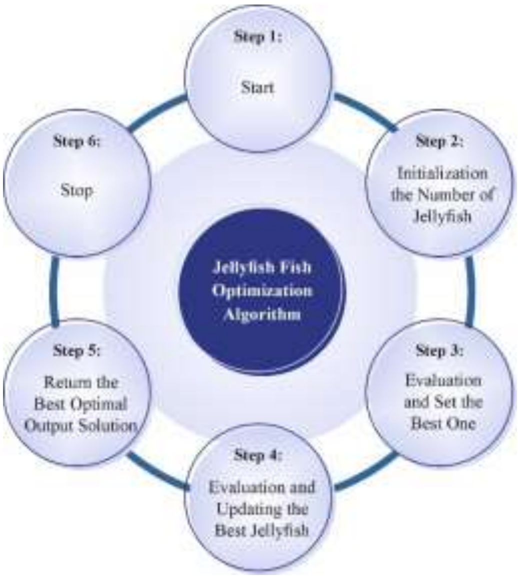

Figure 2: Steps involved in JSA

The FF implemented in the JSA model has been developed for having balance among the count of preferred features in every solution (minimum) as well as classification accuracy (maximum) achieved by employing these chosen features, Eq. (10) indicates the FF to calculate mathematical expressions.

$$Fitness = \alpha\gamma_R(D) + \beta\frac{|R|}{|C|} \tag{8}$$

α and β becomes a 2 parameters with respect to important classification quality and subset length. $\beta = 1 - \alpha$ and $\in [1,0]$. The detection error rate of a specified classifier denoted as $\gamma_R(D)$. $|R|$ represents the cardinality of particular sub-set and $|C|$ refers the overall amount of features in the database.

B. Classification Process

For classification process, RNN-GRU model can be used for the prediction of financial crises. RNN becomes a classical model for sequential data processing and is different from the FFNN, which the RNNs can be the potential to utilize recurrent edges for connecting each neuron to themselves, which enables the likelihood distribution of data series to be modelled at dissimilar time steps [20].

In image classification, assume a data sequence $x = (x_1, x_2, \dots, x_t)$, and include amongst $x_t, t \in \{1,2, \dots, t\}$. Generally, the data at t moment is represented as a vector of input x_t, and the output of hidden layer (HL) at t^{th} time step must be represented by s_t. By using Eq. (1), the output of HL is evaluated:

$$s_t = f(ux_t + ws_{t-1} + b_s), \tag{9}$$

Where the weight matrix at an input to HL is denoted as w, and b_s is the bias vector. The input of the existing time step is x_t, and HL is s_t, the weight matrix prior to the HL of existing time step can be represented as ws_{t-1},

The output layer is formulated by using Eq. (10):

$$\mathrm{o}_t = f(vs_t + b_\mathrm{o}), \tag{10}$$

The RNN faces the long-term dependence problems, viz., challenging to process as well as train long-term data series due to gradient disappears as it transmits in particular time. The LSTM and GRU are applied to resolve these problems. Compared with LSTM, the GRU has lesser parameter and needs less data to be generalized or trained faster. Therefore, the GRU is selected to constitute the RNN model. By using the GRU, the vanishing gradient problem can be overcome while decreasing the training time and model complexity. The RNN encompassed of dual GRU recurrent layers.

The pixel point has been considered as x_t input for pixel-level input of the multi-spectral imageries. The spatial feature vector of images removed through 2D-CNN was considered as the HL of prior time step of h_{t-1} and x_t as input to GRU, thereby getting the pixel-level classification of multi-spectral images. This can be mathematically modelled as follows:

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$$r_t = \sigma(x_t w_r + u_r h_{i-1} + b_r), \tag{11}$$

$$z_i = \sigma(x_i w_z + u_z h_{t-1} + b_z), \tag{12}$$

Here the logistic sigmoid function is $\sigma(\cdot)$, the weight matrices are w_r, u_r, w_z, and u_z, and the bias vectors in the NN is b_r, b_z. x_t is symbolized as $s \times 1$ vectors for pixel-level classification of multi-spectral images, the waveband count denotes s, and we have selected the waveband count as 13, viz., $s = 13$.

The equation for evaluating the candidate's HL is given below:

$$\tilde{h} = \tanh(w_{\tilde{h}} x_t + u_{\tilde{h}}(r_t \odot h_{t-1}) + b_{\tilde{h}} \tag{13}$$

In Eq. (13), $w_{\tilde{h}}$, $u_{\tilde{h}}$ are the weight matrices, $b_{\tilde{h}}$ indicates the bias vector, and tanh $(\cdot)$ is the hyperbolic tangent function. It incorporates the spectral feature data stores in the GRU that fused with the data of update gate for the next computation of HL:

$$h_t = z_t \odot h_{i-1} + (1 - z_t) \odot \tilde{h}, \tag{14}$$

In the GRU, the HL should fed into an output layer, and later the computation of output layer in t time step can be formulated by:

$$y_t = h_t w_q + b_q, \tag{15}$$

In Eq. (15), b_q represents the bias vector, and w_q is the weight matrix.

C. COA based Parameter Tuning

Finally, the COA can be utilized for the optimal tuning of the hyperparameters related to the RNN-GRU model. Khishe et al recently originated COA, a new population based optimizer algorithm derived from the distinct intelligence and motivation of chimps [21]. It is well known for its group hunting. The hunting strategy varies from the others and utilises four dissimilar stages namely driver, chaser, barrier, and attacker correspondingly to explore the search range and these steps are mathematically modelled as follows.

Eqs. (16)-(17) has been used for chasing and driving the prey as follows;

$$D = \left|c.\, a_{prey}(n) - m a_{chimp}(n)\right| \tag{16}$$

$$a_{chimp}(n+1) = a_{prey} - a.\, d \tag{17}$$

Where the number of generations illustrates n, the coefficient vectors are c, m and a computed by the following equations

$$a = 2.\, l.\, r_1 - l \tag{18}$$

$$c = 2.\, r_2 \tag{19}$$

$$m = chotic_{value} \tag{20}$$

Where r_1 and r_2 are random value lies in then range [0,1], m signifies the chotic vector and l used to reduce nonlinearly from 2.5 to 0. Initially, search location is selected by the random value. Next, the four optimum solutions are stored to update the newest location of the search range.

$$d_a = |c_1 a_a - m_1.\, x| \tag{21}$$

$$d_b = |c_2 a_b - m_2.\, x| \tag{22}$$

$$d_c = |c_3 a_c - m_3.\, x| \tag{23}$$

$$d_d = |c_4 a_d - m_4.\, x| \tag{24}$$

Once the random value ranges between [−1,1], then the second location of search individual will be in any location amid its existing position and the position of prey or target

$$x_1 = a_a - a_1.\, d_a \tag{25}$$

$$x_2 = a_b - a_2.\, d_b \tag{26}$$

$$x_3 = a_c - a_3.\, d_c \tag{27}$$

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$$x_4 = ad - a_4 . d_d \quad (28)$$

The location of the search can be computed as follows:

$$x_{n+1} = \frac{x_1 + x_2 + x_3 + x_4}{4} \quad (29)$$

Lastly, Eq. (30) is used for upgrading the position of every members.

$$a_{chimp}(n+1) = \begin{cases} a_{prey}(n) - x.d, if\ \phi < 0.5 \\ chaotic_{value}\ if\ \phi > 0.5 \end{cases} \quad (30)$$

Algorithm 1: Pseudocode of COA algorithm

Inputs: The size of population N and overall amount of iterations t
Set the population $X_i (i = 1,2, \dots, N)$
Where $t < t_{\text{maxiter}}$ do
For every member do
Describe the crowd
By applying is group strategy to upgrade
End for
For every member do
If $x < 1$ then
Upgrade location of existing member
Else if $x > 1$ then
Choose a random member
End if
Upgrade location of existing member
End for
Upgrade $X \approx$ Attacker, Barrier, Driver and Chaser
$t + 1$
End while
Return $X_{attacker}$

The fitness selection (FF) is the significant factor impacting the effectiveness of the MBES method. The hyperparameter selection approach includes the solution encoding algorithm for computing the efficacy of candidate solutions. Here, the MBES model reflects accuracy as the important measure to develop FF that could be expressed as.

$$Fitness = \max(P) \quad (31)$$

$$P = \frac{TP}{TP + FP} \quad (32)$$

From the equation, FP implies the false positive value and where TP describes the true positive value.

4. Result Analysis and Discussion

The performance validation of the JSAFS_ODL model has been verified by utilizing two dataset: German Credit (GC) and Australian Credit (AC) datasets. The GC and AC datasets includes 1000 and 690 samples with dual classes, respectively.

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Table 1: Details on dataset

Datasets	No. of Instances	Financial/Non-Financial Crisis
GC	1000	300/700
AC	690	383/307

Table 2 represents the feature chosen by the JSAFS-ODL technique on two datasets. The JSAFS-ODL approach has selected optimum number of features on both datasets.

Table 2: Features chosen by JSAFS technique

Datasets	Selected Features
GC	1, 2, 4, 6, 7, 10, 13, 16, 18, 19, 20, 21
AC	2, 4, 5, 7, 9, 11, 12

The FCP results of the JSAFS_ODL methodology on two dataset over ten iterations are given in Table 3 and Fig. 3. The outcomes designate that the JSAFS_ODL method reaches better performance. On GC dataset, the JSAFS_ODL model obtains optimal average best cost (ABC) of 0.111 but the HHPODL_FCP, QABO_FS, ACO_FS, and GWO_FS technique provide increased ABC of 0.128, 0.150, 0.156, and 0.168, individually. Besides, with AC dataset, the JSAFS-ODL algorithm gets increased average best cost (ABC) of 0.035 however the HHPODL_FCP, QABO_FS, ACO_FS, and GWO_FS methodology achieves greater ABC of 0.051, 0.060, 0.088, and 0.100, respectively.

Table 3: FCP outcomes of the JSAFS_DL system under two dataset

GC Dataset					
No. of Iterations	JSAFS_ODL	HHPODL_FCP	QABO_FS	ACO_FS	GWO_FS
1	0.109	0.127	0.156	0.162	0.185
2	0.114	0.131	0.154	0.166	0.185
3	0.117	0.132	0.157	0.164	0.163
4	0.116	0.133	0.158	0.165	0.164
5	0.121	0.139	0.160	0.151	0.165
6	0.120	0.135	0.157	0.153	0.166
7	0.119	0.136	0.159	0.152	0.163
8	0.098	0.115	0.138	0.156	0.161
9	0.103	0.119	0.138	0.144	0.164
10	0.097	0.114	0.128	0.145	0.166
Average	0.111	0.128	0.150	0.156	0.168
AC Dataset					
No. of Iterations	JSAFS_ODL	HHPODL_FCP	QABO_FS	ACO_FS	GWO_FS
1	0.043	0.059	0.066	0.086	0.101
2	0.039	0.056	0.067	0.087	0.101
3	0.041	0.059	0.066	0.087	0.101

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4	0.041	0.058	0.070	0.089	0.104
5	0.034	0.049	0.055	0.089	0.100
6	0.034	0.050	0.060	0.087	0.099
7	0.030	0.046	0.055	0.090	0.097
8	0.027	0.044	0.054	0.089	0.101
9	0.029	0.045	0.054	0.088	0.097
10	0.029	0.045	0.057	0.090	0.102
Average	0.035	0.051	0.060	0.088	0.100

The comparison results of the JSAFS_ODL method on GC dataset with recent approaches are shown in Table 4 and Fig. 4. The outcomes imply that LSTM_RNN, ACO, MLP, SVM, and AdaBoost techniques obtain least performance. Besides, the QABO_LSTM-RNN model offers slightly improved results. Although the HHPODL_FCP model reports certainly boosted results. However, the JSAFS_ODL technique gains maximum performance over other models with maximum $sens_y$ of 95.50%, $spec_y$ of 95.50%, $accu_y$ of 95.67%, and F_{score} of 94.65%.

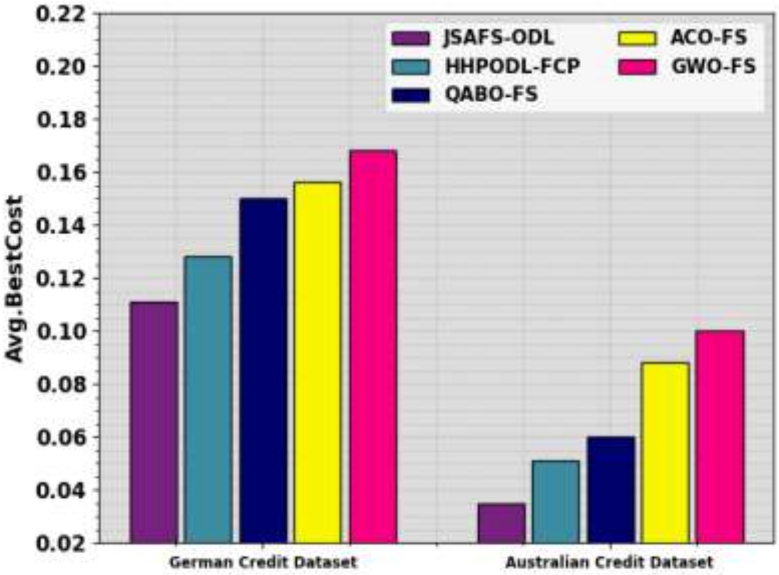

Figure 3: ABC outcomes of the JSAFS_ODL model under two dataset

Table 4: Comparison analysis of the JSAFS_ODL model under GC dataset

GC Dataset				
Classifiers	$Sens_y$	$Spec_y$	$Accu_y$	F_{score}
JSAFS_ODL	95.50	95.50	95.67	94.65
HHPODL _FCP	93.57	94.02	94.93	93.73
QABO-LSTM_RNN	87.23	93.59	91.98	90.12
LSTM_RNN	82.19	88.56	84.58	88.74
ACO	78.32	69.31	75.79	85.41
MLP	73.88	66.88	70.96	75.13

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SVM	72.70	66.44	71.18	71.78
AdaBoost	71.41	61.34	67.54	71.28

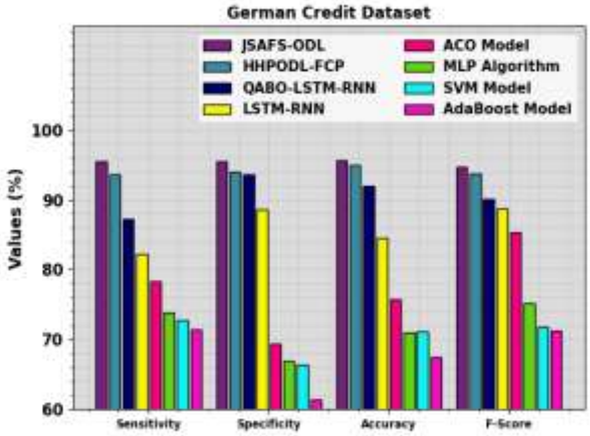

Figure 4: Comparison analysis of the JSAFS_ODL system with GC dataset

The $accu_y$ curves for training (TR) and validation (VL) displayed in Fig. 5 for the JSAFS_ODL system with GC dataset offer valued insights into its effectiveness in diverse epochs. Specifically, it has a reliable improvement in both TR and TS $accu_y$ with raised epochs, specifying the model's proficiency in learning and recognizing patterns at data of TR and TS. The increasing tendency in TS $accu_y$ underscores the model's adaptability to the TR dataset as well as capabilities to generate correct predictions on unnoticed data, emphasizing robust generalized capabilities.

Fig. 6 represents a wide-ranging overview of the TR and TS loss values for the JSAFS_ODL method under GC dataset at abundant epochs. The TR loss dependably reduces as the model refines its weights for diminishing classification errors in both datasets. The loss curves evidently demonstrates the model's alignment with the TR data, emphasizing its abilities for successfully capturing patterns. Significant is the incessant improvement of parameters in the JSAFS_ODL system, targeted at minimalizing discrepancies among actual TR labels and predictions.

Figure 5: $Accu_y$ curve of the JSAFS_ODL model on GC dataset

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Figure 6: Loss curve of the JSAFS_ODL system on GC dataset

The comparison analysis of JSAFS_ODL system on the AC dataset with other algorithms can be evaluated in Table 5 and Fig. 7. The acquired results display that the LSTM_RNN, ACO, MLP, SVM, and AdaBoost methodologies get minimum performance. Moreover, the QABO-LSTM_RNN technique gives moderately boosted outcomes. Then, the HHPODL_FCP method denotes definitely increased outcomes. But, the JSAFS_ODL technique achieves remarkable performance over other algorithms with greater $sens_y$ of 95.13%, $spec_y$ of 95.13%, $accu_y$ of 95.26%, and F_{score} of 94.98% respectively.

Table 5: Comparison analysis of the JSAFS_ODL system under AC dataset

AC Dataset				
Classifiers	$Sens_y$	$Spec_y$	$Accu_y$	F_{score}
JSAFS_ODL	95.13	95.13	95.26	94.98
HHPODL_FCP	94.37	94.61	95.10	94.69
QABO-LSTM_RNN	90.96	93.22	93.37	94.69
LSTM_RNN	86.03	93.07	93.08	91.66
ACO	79.78	89.37	89.71	81.96
MLP	76.54	84.47	84.45	78.75
SVM	71.14	75.71	76.17	77.43
AdaBoost	69.13	67.37	67.71	68.50

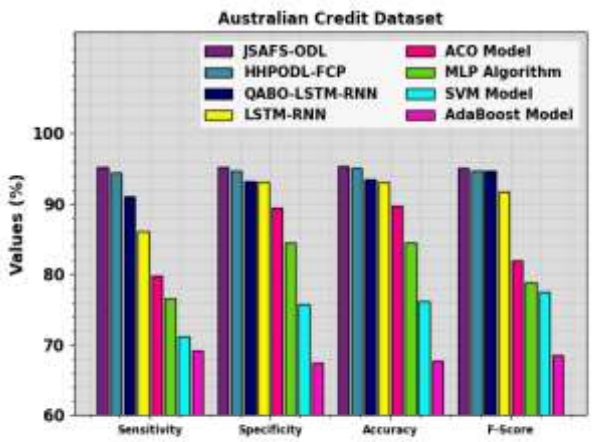

Figure 7: Comparison analysis of the JSAFS_ODL system with AC dataset

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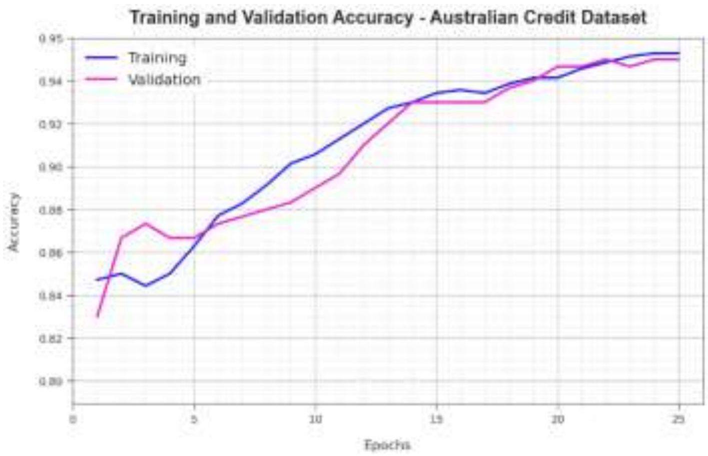

Figure 8: $Accu_y$ curve of the JSAFS_ODL system under AC dataset

The $accu_y$ curves for training (TR) and validation (VL) displayed in Fig. 8 for the JSAFS_ODL method with AC dataset provide respected insights into its effectiveness in varied epochs. Precisely, it has a consistent enhancement in TR and TS $accu_y$ with improved epochs, illustrating the model's proficiencies in learning and determining patterns at both data of TR and TS. The improving tendency in TS $accu_y$ highlights the model's adaptableness to the TR dataset as well as capabilities to produce exact predictions on hidden data, emphasizing robust generalized capabilities.

Fig. 9 shows an extensive review of TR and TS loss values for the JSAFS_ODL algorithm on AC dataset at many epochs. The TR loss reliably minimalized as the model upgrades its weights for lessening classification error. These loss curves obviously reveals the model's alignment with the TR dataset, underscoring its abilities for efficaciously capturing patterns. Major incessant improvement of parameters in the JSAFS_ODL technique, goals at reducing discrepancies among actual and predictions TR labels.

Figure 9: Loss curve of the JSAFS_ODL model on AC dataset

Finally, a comprehensive computational time (CT) results of the JSAFS_ODL technique with recent models on two datasets are stated in Table 6 and Fig. 10. The proficient results displays that the JSAFS_ODL model accomplishes reduced CT values on both datasets. On GC dataset, the JSAFS_ODL methodology offer lower CT of 0.35s while the HHPODL_FCP, QABO-LSTM_RNN, LSTM_RNN, ACO, MLP, SVM, and AdaBoost systems provide increased CT values.

Table 6: CT analysis of the JSAFS_ODL model compared with two datasets

Computational Time (sec)		
Classifiers	GC Dataset	AC Dataset
JSAFS_ODL	0.35	0.58

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HHPODL_FCP	0.73	0.91
QABO-LSTM_RNN	1.71	1.87
LSTM_RNN	2.75	3.83
ACO	1.77	1.90
MLP	3.70	2.90
SVM	1.78	4.84
AdaBoost	2.79	3.97

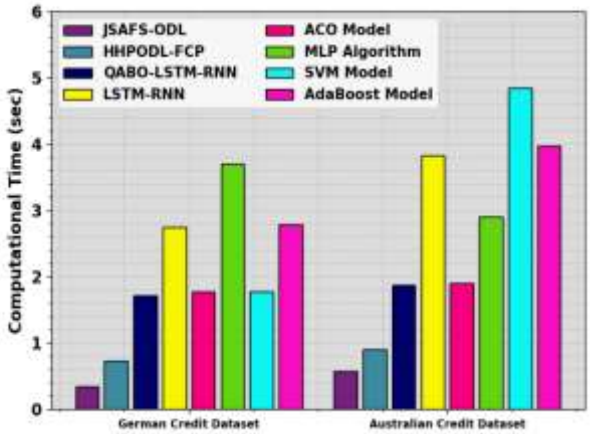

Figure 10: CT analysis of the JSAFS_ODL algorithm compared with two datasets

Meanwhile, with AC dataset, the JSAFS_ODL method gives lesser CT of 0.58s however, the HHPODL_FCP, QABO_LSTM-RNN, LSTM_RNN, ACO, MLP, SVM, and AdaBoost methodologies gains boosted CT values respectively. Thus, the JSAFS_ODL technique is exploited for automated and accurate prediction process in the financial sector.

5. Conclusion

In this manuscript, we have presented a new JSAFS_ODL methodology for FCP. The purpose of the JSAFS_ODL method is to classify the presence of financial crises or non-financial crises. To accomplish this, the JSAFS_ODL approach contains three main processes like JSA based FS, RNN-GRU based classification, and COA based parameter tuning. To accomplish this, the JSAFS_ODL method applies JSA-FS to chosen an optimum features. Besides, RNN-GRU model can be used for the prediction of financial crises. Finally, the COA can be utilized for the optimal tuning of the hyperparameters related to the RNN-GRU technique. To safeguard the better performance of JSAFS_ODL procedure, a series of tests were involved. The obtained values highlighted that the JSAFS_ODL system reaches significant performance.

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