Data-Driven Prescriptive Modelling using Optimized Deep Learning

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Abstract:
This paper proposes an optimized deep learning algorithm for predictive analysis of health care data. The proposed algorithm is a hybrid model of a convolutional neural network and a moth-flame optimization algorithm. The moth-flame optimization algorithm reduces the multi-variant features of the healthcare datasets. the optimized features of the moth flame optimization process in a convolutional neural network. The hybrid model increases the performance of predictive parameters. The proposed algorithm was simulated in MATLAB software and tested on reputed datasets of heart diseases. The performance of the proposed algorithm compares to existing algorithms in deep learning such as CNN, RNN, and GAN. The performance of the proposed algorithms suggests that proposed are very efficient compared to existing algorithms for deep learning
Keywords: Predictive Analysis, Deep Learning, CNN, RNN, GAN, MFO, heart disease.
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1. Introduction

The increasing volume of data poses several issues related to the prediction and processing of analytical results. The major issue of predictive modelling is the selection of features from multi-variant feature data such as health care data, cyber security data, and many more real-time predictions of data. The selection of features empowered the design process of hyper-parameters[1,2,3,4,5]. The accuracy of prediction models depends on the accurate design of hyperparameters. The growing industry 4.0 required more accuracy in the prediction of data. The reported survey suggests that several authors proposed predictive models that were data-driven. Data-driven predictive models are more accurate than independent predictive models such as artificial neural networks, machine learning models, and deep learning models. Industry 4.0's main goal today is to address challenges like the need for systems that are flexible and robust against unforeseen circumstances, as well as a level of autonomy that is still lacking. Like its predecessors, this industrial revolution is supported by pillars that outline the principles on which it should be built, with the main goal of transforming isolated components into an integrated, automated, and optimised production flow[6,7,8,9]. In addition to changing the producer-customer relationship paradigm, this transformation results in greater efficiency when compared to "traditional" processes[10,11,12]. This is because the final product is more in line with the customer's needs and doesn't require as much adaptation. Big data, simulation and virtual reality, system integration, cloud computing and cyber security, additive manufacturing and process automation, and the industrial internet of things are thus the key pillars. Machine learning and conventional neural network models affect the accuracy of predictive mining and predictive modelling of business processes. The nature of the machine learning model is just like a black box, and the prediction results are compromised[13,14,15]. The incremental development of machine learning algorithms such as deep learning and capsule networks improves the decision support system in business processes and grows the industry. Despite several models of machine learning and deep learning, the accuracy of predictive modelling is still a challenging task. Recently, several authors proposed optimisation-based predictive model design. The optimisation-based predictive model design follows the concepts of feature selection and optimisation. The feature optimisation process reduces the lower content of features as noise in the data. The reduced features increase the mapping ratio of dedicated classes in the model and increase accuracy and other parameters of modelling. Most of the authors employed deep learning algorithms such as GAN, CNN, and RNN. Convolutional neural networks (CNN) dominate deep learning algorithms and boost the prediction accuracy of modelling data-driven applications. The objective function of the CNN algorithm is to increase the number of layers and matching points of class. Further recurrent neural network (RNN) feedforward neural network algorithms also increase the prediction ratio of business models[16,17,18]. Also, generative adversarial networks (GAN) are very popular for predictive mining in multimedia data and other signal processing applications. The modelling approach to mining focuses on feature extraction and optimisation. The maximum features optimisation algorithms embedded with deep learning algorithms. This paper proposes an optimised deep learning algorithm for predictive mining of health care data. The proposed algorithm employed the moth flame optimisation (MFO) algorithm along with a convolutional neural network to increase the prediction of health-care data. The rest of the paper is organised in Section II as related work; Section III describes proposed methodology; Section IV analyses experimental results of proposed and experimental algorithms; and finally concludes in Section V.

2. Related Work

The continuous efforts of algorithm development in predictive modelling increase prediction accuracy and business reliability. Continuous efforts focus on machine learning and the advancement of machine learning algorithms. This section explores the recent development of algorithms in predictive modelling in real-world applications and emerging industries. According to the author [1], improving genomic prediction methods opens the possibility of more effectively integrating physiology-based selection strategies into various agro-ecological and agro-management systems. When comparing genotype SY performance in row spacing treatments, 69% had superior SY response at 38cm, while 31% had greater SY at 76 cm row spacing. The author [2] promotes a methodology that is capable of assisting portfolio management in making the best decision to design the product portfolio in accordance with a holistic framework. The author [3] discusses efforts to provide a framework for predictive and prescriptive governance, with the goal of supplying information to help policymakers make well-informed and fact-based decisions. According to the author [4], the primary goal of this effort is to create a new LSTM tool for forecasting flood dispersion over By using test scenarios related to the Kushiro-Tsunami, the performance of the LSTM-ROM produced here has been According to the author [5], these tactics include, among other things, developing a predictive model to pinpoint workers who are likely to leave. This section provides a summary of some of the more important subjects that will probably come up when implementing various HRA initiatives. The author [6] suggests a smart wearable that uses biometrics to analyse a person's emotional state and forecast the likelihood of a subsequent impulsive outburst. In 93% of the cases, the experimental subject was within 10 minutes and in 82% within 5 minutes of the anticipated time. According to the author [7], a variety of decision problems can be solved using suggested solution approaches, which are modelled after machine learning (ML) techniques such as local regression (LOESS), classification and regression trees (CART), and random forests (RF). According to the coefficient of prescriptiveness, this methodology accounts for an 88% improvement. In [8], the authors explore why next-event forecasting is insufficient for practitioners. In light of this, this work-in-progress study suggests a method for selecting the process-representative next best action. In [10], the authors use of PPA in healthcare is also examined from the perspectives of various stakeholders. The findings show that the stakeholders pursue divergent interests, necessitating governmental control to allow PPA to spread widely. In [11], the authors explore 12 ANN models that were used in a comparative analysis to determine which ANN method would be most effective for estimating the target function. The outcomes demonstrated that 6 and 10 neurons in the first and second hidden layers, respectively, were the optimal topologies for the two-hidden layer ANN. In [12], the authors employed the power plant's preventative maintenance and diagnosis of its flame tube as an illustration of the methodology. The neural network was trained using the physics-based model in a variety of malfunctioning flame tube scenarios, and it obtained an accuracy of greater than 0.95. In [13], the authors proposed an algorithm based on GGNNs, which are ideal for describing a business process's sequential flow. After 548 epochs and using the previously mentioned setup, we had an accuracy by the total number of classifications of 77.00%. In [14], the authors provide a description of the current issue and a suggested approach for figuring out the best order numbers for products in multi-item inventory management. The effectiveness of the suggested strategy is examined by various analyses, and the following crucial findings are noteworthy here: In [15], the authors proposed model outperformed the benchmark techniques, which comprised buy-and-hold trading strategies, multiple linear regression, trading, and analyst predictions. The ANN methodology used to make the predictions achieved accuracy performance scores of up to 60%. In [16], the authors employed significant e-commerce platforms and provided two real-world datasets that were used to evaluate the proposed framework. In comparison to standard industry practise, the results show that the decision support framework is beneficial in providing delivery cost savings of up to 10.6%. In [17], authors proposed a holistic end-to-end prescriptive maintenance framework (HeePMF) that combines equipment and operational data, analysis of maintenance needs, and feedback with predictive technology to produce insights that can be put into practise. In [18], authors explore cutting-edge techniques to forecast a business process' future performance at the level of the process model. To be more specific, they build an annotated transition system and use it to produce a process representation matrix. In [19], the authors employed control-flow conformity, which is ensured by this technique's use of business process simulation. The recommendation of more sophisticated next-best actions can be facilitated by more powerful multi-tasking DNN systems. In [21], the proposed methodology can be used as a support software tool for recruiters and HR managers and can be applied directly by HR professionals without the requirement for more in-depth technical or machine learning understanding. The author [22] proposed generic functional and non-functional models for prescriptive recommender systems. The author [23] employed shift winding operation data parameterization and combined it with configuration data to enable behaviour-based management of robotic remanufacturing using vector mapping and deep neural learning. For random wires, the dense Orth cyclic winding provides the highest packing density of 90.7%. The author [24] proposed predictive models and evaluated them in an offset well in the North Sea using a strict data processing and modelling methodology. Yet, in comparison to the earlier casing departure tasks, the TOB values often dropped by only 2%. The author [25] employed data processing, cleaning, and ingestion into databases; automated machine learning (Auto ML) applications to produce an accurate machine-learning model; and numerical optimisation of decision parameters to minimise an economic objective. Savings of 5 to 32% on well completion costs were attainable while keeping production levels the same. The author [26] contributes to IS-related developments as a prescriptive science by identifying meaning-sending connections. They define a collection of integrative research techniques that take place at the explanation-prescription nexus, the intersection of explanatory, predictive, and prescriptive science. The author's [27] focus on empirical study examines the accuracy of the suggested strategy on various benchmark outcome prediction problems in comparison to leading-edge rival approaches, demonstrating its viability. The author [29] proposed machine learning (ML) algorithms to explore nonlinear correlations among data variables, which is one reason why they are being used more and more for predictive analytics. The author [30] proposed a novel approach to optimisation in the WWTP area: long-short-term memory (LSTM) artificial neural networks (ANN) combined with genetic algorithms (GA). According to the author [31], they outline the method's structure and use simulated data to compare its performance to more established techniques like point-estimate-based optimisation, stochastic optimisation, and recently discovered machine learning-based optimisation techniques. The author's [32] proposed model can automatically create the daily plan for the interpreter, saving the hospital a lot of time. The author's [33] employed real-world use cases made possible by a classification model for the detection of product movements on the store floor; we look at electronic article monitoring and automated checkouts. Ensemble techniques and different algorithmic strategies may assist in developing a more trustworthy detection system by increasing prediction power even further. The author's [34] proposed approach assesses customer interruptions in terms of probability distributions. Contrary to the traditional BMA technique, the suggested algorithm bases the base learner weights on a multinomial logistic function of the data. The author [36] employed advanced prediction analysis utilising prescriptive analytics to offer real-time, effective solutions to any stock market user. Even though the present systems predict stock using multiple methodologies and algorithms, the proposed system's prediction methodology, however, has been successful in reducing the accuracy gap by a maximum of 0.93%. The author [37] proposed model-based information systems and process models, which were the centre of conventional BPM research, to data-driven techniques like process mining. The author's [39] proposed Max UpTM Fleet, created by LSA, is a vehicle fleet asset management system that will reduce unplanned breakdowns by 70% to 75% and give a 35% to 45% reduction in downtime.

The author's [40] employed algorithms have an area under the receiver operating characteristic curve of 0.82 and an average precision of 84.2% in predicting fraudulent behaviour.

3. Proposed Methodology

This section describes the proposed methodology for predictive analysis using an optimised deep learning algorithm. The process of feature optimization employs the moth flame optimisation (MFO) algorithm. Moth Flame Optimization is a bio-inspired meta-heuristic, dynamic population-based optimisation algorithm. The employed MFO algorithms reduce the content of multi-variant features in the data. the optimized data process through the convolutional neural network algorithm and predictive results of the data. The processing of algorithms is described in two sections: the first section describes the MFO algorithm and feature optimization, and the second section describes the employed CNN algorithm.

1st section

Moth-flame optimization algorithm is dynamic population based meta-heuristic function. The processing of algorithm describes here[28]

The set of moths is defined as M, in which Mi is the i-th moth and Mij is the corresponding position of the i-th moth. Now OM define as fitness constraints

$$M = \begin{pmatrix} M \\ . \\ . \\ Mi \end{pmatrix} = \begin{pmatrix} M1 & & M1j \\ & . & \\ & . & \\ Mi1 \dots \dots \dots & & \dots Mij \end{pmatrix}$$

The set of flame is defined as F, in which Fi is the i-th flame and Fij is the corresponding position of the i-th flame. Now OF is define as fitness constraints

$$F = \begin{pmatrix} F \\ . \\ . \\ Fi \end{pmatrix} = \begin{pmatrix} F1 & & F1j \\ & . & \\ & . & \\ Fi1 \dots \dots \dots & & \dots Fij \end{pmatrix}$$

The algorithm describes the global optimal solution as

$$MFO = (I, P, T) \dots \dots \dots \dots \dots \dots \dots \dots \dots .. (1)$$
$$I: \varphi \to \{M, OM\} \dots \dots \dots \dots \dots \dots \dots \dots .. (2)$$
$$P: M \to M \dots \dots \dots \dots \dots \dots \dots \dots \dots .. (3)$$

$$T: M \rightarrow \{true, false\} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

The processing of algorithm as

M=I()

While T(M) is equal to false

M=P(M);

End

Update the position of flames as

Mi=S(Mi,Fi)……………………………………………….(5)

$$S(Mi, Fj) = D_{ie^{bt}} \cos(2\prod t) + Fj \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (6)$$

$$Di = |Fj - Mi| \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (7)$$

The flame is updated as

$$flame\ no = round\left(N - L\frac{N-1}{T}\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (8)$$

Where N is number of initial flames, T is total number of iterations, and L is current number of the iterations.

Processing of MFO algorithm

Define value of M according to formula (2) and estimate OM as M

The position of M and OM is constant and F and OF can be found by matching sequence of M and OM

By formula (8) estimates the numbers of moth and the end moths' flames removed

The distance between moths is calculated by formula (7)

Update the value of moths according to formula (6)

By M estimate OM

Decide the end condition is met, otherwise go to step 2

The process of feature selection describes here

The feature set of data mapped as $(X_i \in R^D, y_i \in R)$,i=1……………….m

Here Xi is feature set the range between 0 to 1, R is relation belongs to data.

$select\ X(f)$ if $*= X$

$[x^1, \ldots\ldots x^k] \leftarrow [rand(1, k) \times (p - w)] + 1$

$f \leftarrow n$ the optimal features of set

For $i \leftarrow 1\ \ to\ 41\ do$

$f^{\cdot} \in X^D \leftarrow S *= X$
$41_*^i \in R^D \leftarrow moth\ baise$
$G \in R^D \leftarrow set\ of\ features$
End for

Input sample of features as $x_*^1, \dots \dots .. x_*^m$
$F_{MFO} \in R^{D \times x} \leftarrow \emptyset([x_*^1, \dots \dots .. x_*^m]) \quad w = new\ feature\ set$
$W \in R^D \leftarrow x^{-1}$
$F \in R^d \leftarrow W^T\ \emptyset(G)$
For $optimal \leftarrow 1\ to\ AX_c\ do$
Optimal feature set

2nd section

The proposed algorithm of predictive system using the principle of data-driven. the proposed CNN model encompasses M=3. The design of class target and non-target of health care data. The activation function of algorithm is RLU and their basic value is 1. The processing of algorithm describes here. the network define relationship between two non-linear variables K and Ki+1 through network function as

$$Ki + 1 = \delta(wki + b) \dots \dots \dots \dots \dots \dots \dots \dots (9)$$

Where δ is activation function and matrix W and b is called model parameters. The variable K and ki+1 is from of layers. the multilayer neural network argumenta with advance learning called deep neural network. The classification of network defines as y=f(u). the process of network function defines as

K1= $\delta 1$(w1u+b1)

K2= $\delta 2$(w2p1+b2)

....

....

Y= δL(wLpL-1+bL)

Where L is number of layers

Process of training of CNN.

The relation of neurons defines the process of data

$T_k : X^{n_x} \rightarrow C^{n_x}$, where $x_k \in T^{n_x}$

Be the set of data in neurons for the processing.

Hypothesis of error estimated by E

$$E_j = H_j\left(x_j\right) + v_j, \quad \forall\, k \le j \le k + A$$

where $H_j: R^{n_x} \rightarrow R^{n_y}$ is the relation of multilayer input?

estimate trained pattern

$$x_k = F_0 \rightarrow k(x_0) + \xi k$$

define learning factor as

$$x_k = arg\min_x \left\{ \|x - x_k\| \, B_k^{-1} + \sum_{j=k}^{k+A} \|H_j F_j(x) - y_j\| R_j^{-1} \right\}$$

Algorithm

Define $i = 0$

while $i < L$ do

process the data and M is vector of convergence

$$\{x_k \, \mathrm{I} \, k \in [M \,.\, i, M \,.\, (i+1)]\}$$

$$x_k = arg\min_x \left\{ \|x - x_k\| P_k^{-1} + \sum_{k}^{k+p} \|H_j \, M_j, (x)\| p_j^{-1} \right\}$$

Vote the class of classifier

Class $= \{Fs(x_{k-1}), \; x_k\}$ with $k \in [i.M, (i+1).M]$

Measure i for next step

end

Output: $accuracy$.

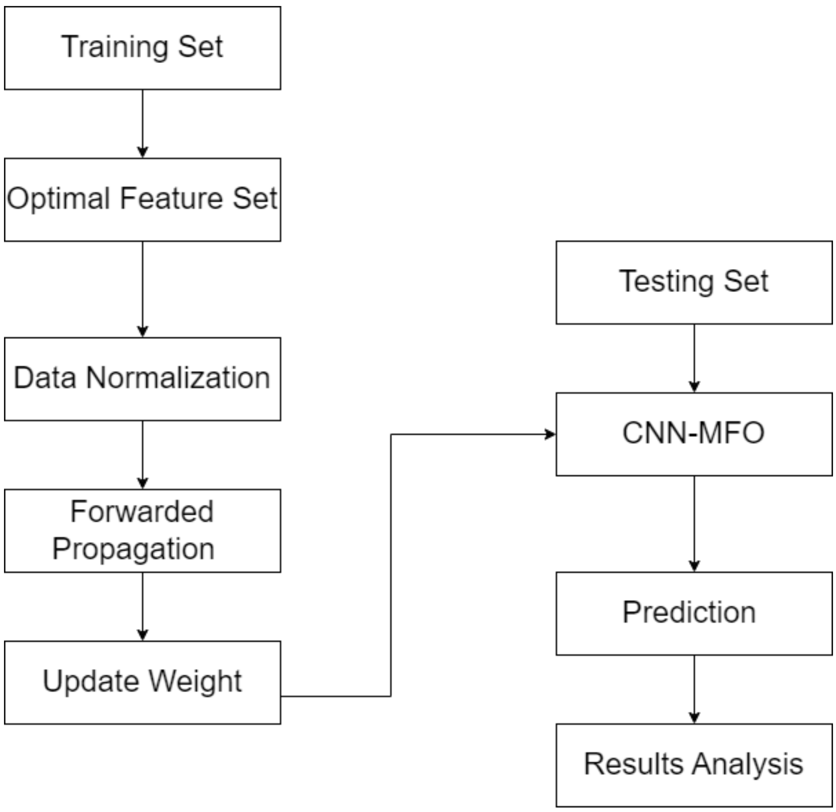

Figure 1 proposed model of predictive analysis of optimized deep learning

4. Experimental Analysis

To evaluate the performance of the proposed algorithm, MATLAB software is used for the simulation process. The efficiency of the proposed algorithm is evaluated using parametric measures like accuracy, specificity, and sensitivity. By the confusion matrix, estimate the value of prediction as true positive (TP), true negative (TN), false positive (FP), and false negative (FN)[9,38,20].

Sensitivity- Precision measures the proportion of predicted positives/negatives which are actually positive/negative.

$$Sensitivity = \frac{TP}{TP + FN} \times 100 \ldots\ldots\ldots\ldots\ldots\ldots(10)$$

Specificity -It is the proportion of actual positives/negatives which are predicted positive/negative.

$$Specificity = \frac{TN}{TN + FP} \times 100 \ldots\ldots\ldots\ldots\ldots\ldots(11)$$

Accuracy-It is the proportion of the total number of predictions that were correct or it is the percentage of correctly classified instances.

$$Accuracy = \frac{TP+TN}{TP+TN+FN+FP} \ldots\ldots\ldots\ldots\ldots\ldots(12)$$

Dataset

To validate the proposed algorithm, used several datasets of heart disease and intrusion detection system. The source of dataset is UCI machine Learning Repository. All dataset free available for study purpose. The description of dataset mention below [40].

Cleveland

This database contains 76 attributes, but consider only of 14 of them. The total number of instances is 303.

Z-Alizadeh Sani[35]

This dataset contains 270 instance and 13 attributes. Each patient could be in two possible categories CAD or Normal. A patient is categorized as CAD, if his/her diameter narrowing is greater than or equal to 50%, and otherwise as Normal.

Statlog[36]

This dataset has been 270 instance and 13 attributes. The missing attribute of dataset is null.

Table: 1 Comparative performance analysis of CNN, RNN, GAN and Proposed method and estimated parameters as accuracy, sensitivity, specificity.

	Method	Accuracy	Sensitivity	Specificity
CLEVELAND	CNN [36]	86.43	85.72	86.97
	RNN [35]	86.62	85.68	85.74
	GAN [15]	87.45	86.54	85.98
	PROPOSED	89.91	88.74	87.69
Z-ALIZADEH SANI	CNN [36]	88.22	87.45	86.46
	RNN [35]	87.35	87.69	86.15
	GAN [15]	87.54	86.67	85.87
	PROPOSED	89.93	88.62	87.79
STATLOG	CNN [36]	88.92	87.79	86.29
	RNN [35]	87.68	86.28	85.39
	GAN [15]	87.97	85.77	84.34
	PROPOSED	90.85	89.48	88.91

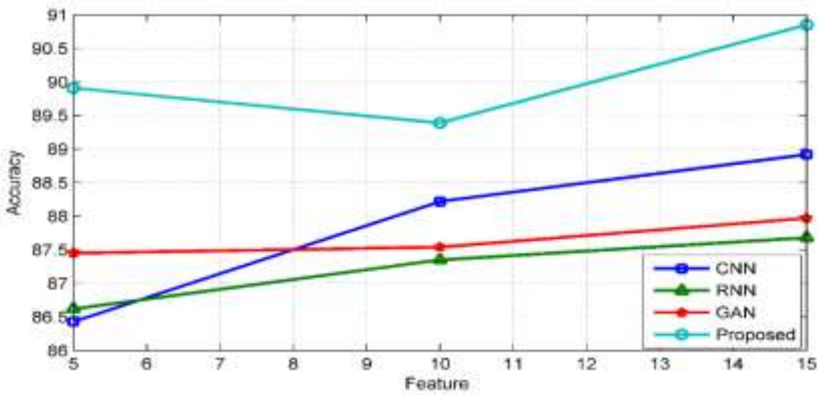

Figure: 2 Comparative performance of CNN, RNN, GAN and Proposed of accuracy of dedicated dataset.

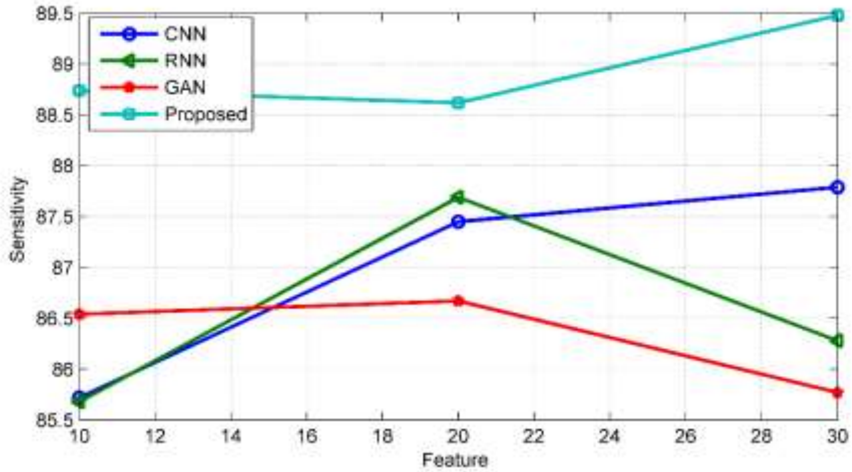

Figure: 3 Comparative performance of CNN, RNN, GAN and Proposed of sensitivity of dedicated datasets.

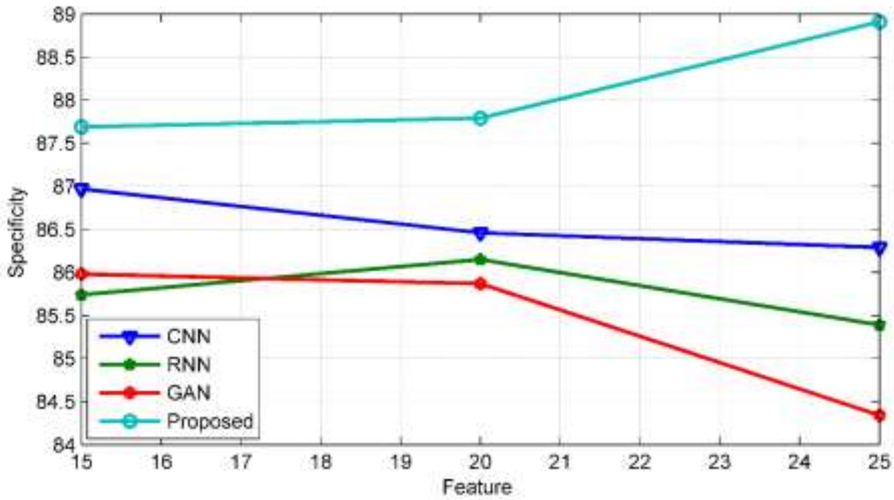

Figure: 4 Comparative performance of CNN, RNN, GAN and Proposed of specificity of dedicated datasets.

5. Conclusion & Future Scope

The proposed algorithm increases the accuracy of predictive analysis of health-care datasets. To increase algorithm precision and produce findings that can be trusted, more precise feature selection techniques are applied. If a specific form of heart disease is identified, the patient should get care tailored to that illness. In essence, we would draw the conclusion that a dataset of acceptable samples and trustworthy data will be utilised to generate a heart disease prediction model. The dataset must be pre-processed as a result, since feature optimisation is the most important step in getting the dataset ready for the deep learning algorithm and improving outcomes. For a predictive model to produce reliable results, a suitable algorithm must be utilised. Our proposed algorithm has achieved 88.84%, 89.44%, 91.56%, 92.72%, and

94.16% accuracy based on the different heart disease datasets. The correct classification probability of cardiovascular disease of the proposed algorithm has been pointed out by the analysis of the results. The proposed algorithm has also gained better accuracy, i.e., 98.88%, 99.53%, 99.98%, 96.66%, 97.77%, 98.36%, 99.56, and 94.37%, based on different partitions of the Cleveland, Hungarian, Cleveland-Hungarian (CH), and Cleveland-Hungary-Switzerland-Long datasets. The suggested methodology has shown improved performance compared to other deep learning models.

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