CHAOTIC GIANT TRAVELLY OPTIMIZER BASED FASTER REGION BASED CONVOLUTIONAL NEURAL NETWORK FOR THE RISK PREDICTION OF DIABETES DISEASE IN NORTH KASHMIR

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Abstract
Diabetes is a chronic disease that occurs due to the rise of blood sugar level. The reason for diabetes varies with patients and in North Kashmir it rising now-a-days. To analyze the prevalence and risk of diabetes in North Kashmir we have conducted the study among 1023 people and collected the data for further processing. From the collected data we have predicted the risk of diabetes with innovative approaches. The prediction of disease by various approaches shows higher prediction loss, lower training speed with higher computational complexities. To overcome these issues, in this work we propose a deep learning based approach for Diabetes Disease Risk Prediction in North Kashmir. In this work, the data is pre-processed using Guided anisotropic difusion filtering (GADF). Subsequently, the feature extraction is performed using novel Young's double slit experiment optimizer (YDO) based discrete cosine transform (DCT). Meanwhile, the risk prediction is carried out using Chaotic Giant Trevally Optimizer (CGTO) based Faster Region based Convolutional Neural Network (Faster-RCNN) approach. Experimental demonstration is carried out using Python and analyzed various performances and made an analogous study with state-of-art works. The statistical analysis shows that the proposed approach can be easily used for the prediction of diabetic disease from data.

Keywords: Diabetes risk prediction, north Kashmir, Faster RCNN, Chaotic Giant trevally optimizer, and DCT.

1. Introduction:

Diabetes [1] used to be brought on by an overabundance of glycogen in the body's circulatory system. Long-term maintenance of the same situation causes serious harm to blood vessels. An individual with diabetes is susceptible to impaired renal function, vision loss, tooth bleeding, amputations of lower limbs, nerve problems, and other conditions. In diabetics, it also increases the risk of stroke and coronary artery disease. The kidney's renal cells are destroyed, which causes neuropathy due to diabetes, while the cerebellum's synapses have been harmed, which causes diabetic retinopathy (DR) [2], which causes macular inflammation. According to a poll conducted by the World Health Organization (WHO) [3], diabetes would rank seventh among lethal diseases.

According to the new statistics, there were approximately 108 million people with diabetes participated in the past, but that number has now climbed to 422 million. According to data, the percentage of adults over 18 who have diabetes has increased from 4.7% to 8.5%, those who are the less fortunate people are more likely to get diabetes, and around 61.3 million Indians between the ages of 25 and 75 are reported to have diabetes. As a substitute, it claims that by 2030, they might reach 101.2 million, the retina will be affected if the amount of glucose in the blood often rises. Extreme glucose [4] elevation significantly impacts the flow of blood vessels, weakening the system that controls vision in humans and causing blood to leak from the eyes.

Nevertheless, the power to cure sickness is acquired by people, if the brain notices an arterial blood leak, it usually stimulates the nearby tissues to control the situation. It, therefore, triggers the haphazard growth of new arteries and veins [5], although the resulting cells are dehydrated in appearance. The earliest stage of the condition gradually impairs eyesight. As a result, diabetic individuals are required to have a routine eye exam during which an ophthalmologist ought to examine the innermost layer of the retina. The condition results in persistent eye damage and, in some cases, vision loss owing to problems with diabetes mellitus [6]. If this sort of patient issue is not addressed, there is a great probability that the patient may go blind. When suffering from diabetes, the system generates insufficient insulin or uses it improperly.

It is a persistent illness which influences how the human body converts nutrients into activity. The body converts most of the food you consume into sugar, also known as glucose, which is then released into the circulatory system. Investigators assume it is a condition called autoimmune disease in which the body unintentionally kills the pancreatic cells that make insulin. Insulin [7] is normally secreted into the circulation by the organ known as the pancreas. As the insulin moves through the human body, glucose enters the cells. Diabetes treatment frequently includes taking insulin therapy or other diabetic medications. Antibiotics can assist you in treating the condition in addition to choosing nutritious foods and beverages, engaging in physical exercise, getting adequate sleep, and overseeing anxiety.

There are also some more therapy choices accessible. Destruction of the arteries and veins and the spinal nerves that regulate the circulatory system can result in cardiovascular disease and stroke. Kidney disease is brought on by the kidneys' blood arteries being damaged. High blood sugar [8] levels often develop in diabetics. It may result in sensations including extreme dehydration, frequent urination, and fatigue. Additionally, it may make you more susceptible to developing major heart, nervousness, and retinal problems. It's a chronic ailment that might have an impact on everyday activities. Patients could need to adjust their eating habits, take medication, and have frequent examinations. The prediction of diabetes from the collected data is very intricate and many approaches have been stated to predict the disease. Nevertheless, most of the works were affected with computational complexities, lower training speed with higher memory usage and higher prediction loss. Hence to overcome these issues, we proposed a novel CGTO based Faster RCNN approach. Main contributions are listed further,

- About 1023 patients' data are collected from the North Kashmir to analyze the prevalence diabetes and considered 8 attributes.
- The collected data are pre-processed to transform the imbalanced data into balanced data with the assistant of GADF approach. The features are extracted using the YDO-DCT approach and used for further prediction purpose.
- The extracted features are predicted as healthy and diabetes using the proposed CGTO-Faster RCNN approach. In the Faster RCNN itself the extracted features are selected using the backbone layer for mapping.

The remainder of the work is organized as follows, in section 2 the relevant works are analyzed and highlighted the advantages and demerits. In section 3 the materials and method section is explained. The proposed approach for the risk prediction of diabetes disease among north Kashmir people is explained in section 4. The result and discussion portion is shown in section 5. The conclusion of work is briefly explained in section 6.

2. Literature survey:

Shankar et al. [9] have described Hyperparameter Tuning Inception-v4 (HPTI-v4) model to identify and identify Diabetic retinopathy from color retinal pictures. It is made up of an array of components, including preliminary processing, segmentation, extraction of features, and grouping. Here, the suggested content extract approach is predicated on segmenting procedure using histogram-based classification. For the categorization of DR pictures, the model may be that used as an electronic assessment tool. This method worked more efficiently and accurately. Hence, it is insufficient to use the classification models.

Sarki et al. [10] have presented a Deep Convolutional Neural Network (DCNN) depending automated diabetic eye disease classifier that can differentiate between photos of healthy people and those with disease disorders. To increase sensitivity for the various classes, they developed and evaluated moderate and multi-class identification scenarios, including various initial processing and enhancement procedures that would boost the preciseness of the outcomes while improving the suitable quantity of samples for the information

being analyzed. Therefore, the use of a single data-collecting platform makes it difficult to validate specific forecasts.
Gadekallu et al. [11] have implemented a deep neural network model to categorize the data collection's retrieved characteristics for retinopathy associated with diabetes. The dataset was converted, normalized, and abnormalities were eliminated using the conventional scaler procedure, which was employed by the framework. Attribute extraction was then carried out to identify pertinent variables from the information set. The total quantity of variables was raised by dynamically repeating the information to improve the accuracy of the framework. Hence, it is inadequate to use bigger collections of data with greater parameters.
Reddy et al. [12] have evaluated Machine learning algorithms and the outputs of two ground-breaking approaches for minimizing dimensionality: the principal component approach and linear discriminant evaluation. A continuous sample was used to conduct an initial evaluation in the present moment. They examined two approaches employing horizontal assistance and the standard sequential correlation duration for determining the features of one patient's condition. The findings collected demonstrate that the suggested classifier outperformed standard systems. Additionally, these methods may be used to solve more complicated algorithms.
Hasan et al. [13] have modified Machine Learning (ML) classifiers to enhance the forecasting of diabetes. Preprocessing, which includes exception denial, completing in the gaps, data consistency, selecting features, and K-factor double-validation, is at the core of the suggested pipeline's contemporary outcome. Considering specific it has an elevated downward slope towards the middle point of that variable dispersion, the average figure in the unfilled place of the feature is preferable to the midpoint values. It can deliver superior outcomes on the same dataset, which can improve diabetic accuracy in prediction. Hence, there is a lack of predicting illness classifications.
Maniruzzaman et al. [14] have developed a machine learning (ML) depending method for forecasting patients with diabetes. Our theory was used in a predictive nature system employing the decision-making approach, and the classifier provided the best level of precision in identifying features. Our findings showed that the accuracy of the suggested mixture for the K10 procedure was 94.25%. Therefore, it is an inconvenient and inexpensive alternative for both diabetes people and medical professionals.
Zhou et al. [15] suggested a Deep Learning for Predicting Diabetes (DLPD) model for the diagnosis of potential illness kinds and early detection of insulin resistance. The concealed portion of the neural structure is eliminated by the DNN to accommodate a certain quantity of simulated data and modify all the weights as well as the biases at a specific moment throughout the slope descent iteration process utilizing data. Since there were few intervals in the initial phase, the approach will operate quickly on any portable platform. Hence, the Opportunity of developing traits is typically disregarded by medical professionals.
Theis et al. [16] highlighted deep learning architecture to enhance current intensity grading techniques by using diabetic individuals with medical conditions. To transform online medical records into an administrative stream structure suited for process analysis and how to utilize this data to forecast patient outcomes. In addition to prior surgical procedures, the suggested method makes use of characteristics, medical evaluations, and therapies, assessments of the health of people with diabetes. The technique produced greater accuracy and precision. Thus, evaluation of the method's viability in a clinical environment was not taken into account. The literature surveys of different approaches are listed in table 1.

Table 1: Literature surveys of several approaches

Reference	Method/ Algorithm	Performance metrics	Limitations
Shankar et al. [9]	Hyperparameter Tuning Inception-v4 (HPTI-v4)	Efficient and accurate	Inadequate classification models

Sarki et al. [10]	Deep Convolutional Neural Network (DCNN)	Improves the quality of data	challenging to validate accurate forecast
Gadekallu et al. [11]	deep neural network	Improves accuracy	inadequate to use bigger collections of data
Reddy et al. [12]	Machine learning algorithms	Efficient to classify standard systems	Complicated to solve
Hasan et al. [13]	Machine Learning (ML)	Improves accuracy	Lack of predicting illness classifications
Maniruzzaman et al. [14]	machine learning (ML)	Greater performance	inconvenient and inexpensive
Zhou et al. [15]	Deep Learning for Predicting Diabetes (DLPD)	Quick and portable	Medical experts usually dismiss the possibility of acquiring features.
Theis et al. [16]	deep learning	greater accuracy	It was not considered to determine the method's applicability in a clinical setting.

3. Materials and Methods

This section is used to present the diabetic dataset collection for the analysis of disease risk predictions in the North Kashmir along with the attributes. The details are explained below.

3.1 Dataset Collection

The data are collected from the various hospitals of north Kashmir with the collaboration of many diabetic specialists. For collecting the data we have utilized snow sampling technique and collected 1023 instances with 9 attributes that are listed in table 2. Any personal data are not included to protect the privacy of the patients; however, the data are imbalance in nature and can be balanced with the pre-processing techniques. Moreover, the data are gathered during the years from March 2022 to may 2023.

Table 2: Attributes of patients taken for the risk prediction of diabetic disease

Sl. No	Attributes	Description	Range/ Unit
1.	Age	Age of the patients	Years
2.	BS-F	Blood sugar at the fasting stage	Mg/dL
3.	BS-AF	Blood sugar after having food	Mg/dL
4.	ST	Sleep time of the patients	Hours
5.	Sex	Sex of the patients	F/M
6.	BMI	Body mass index	Kg/m^2
7.	Diastolic BP	Diastolic blood pressure measurement	mmHg
8.	Systolic BP	Systolic blood pressure measurement	mmHg
9.	Exercise time	Time spend by patients for doing exercise	Hours

Age is one of the risk factors of diabetes; people more than 45 years are more likely to affect with the same. Meanwhile male are twice as chance as affected by the disease than the female. The physical activities like exercise will help the patients to reduce the blood sugar level and thus avoid the diabetes. Maintaining the weight also help to prevent the diabetes among the aged as well as young people.

4. Proposed Methodology for the Risk prediction of Diabetes Disease among North Kashmir people

To predict the risk factors of diabetes disease among the north Kashmir people we have taken different approach as shown in figure 1. After the data is collected from various hospitals, the data are pre-processed to make the data balanced with the Guided anisotropic difusion filtering (GADF). This also removes the unwanted data and noises from the dataset. Meanwhile, the required features for the risk prediction of diabetes we have utilized the novel discrete cosine transform (DCT). This effectively extracts the features from the dataset. The Improved Giant Trevally optimizer (IGT) based Fast-RCNN (IGT-FRCNN) is used for the prediction of diabetes from the extracted features as normal and diabetes. Subsequently, statistical analysis is effectuated to ensure, the efficacy of the proposed work over other state-of-art works.

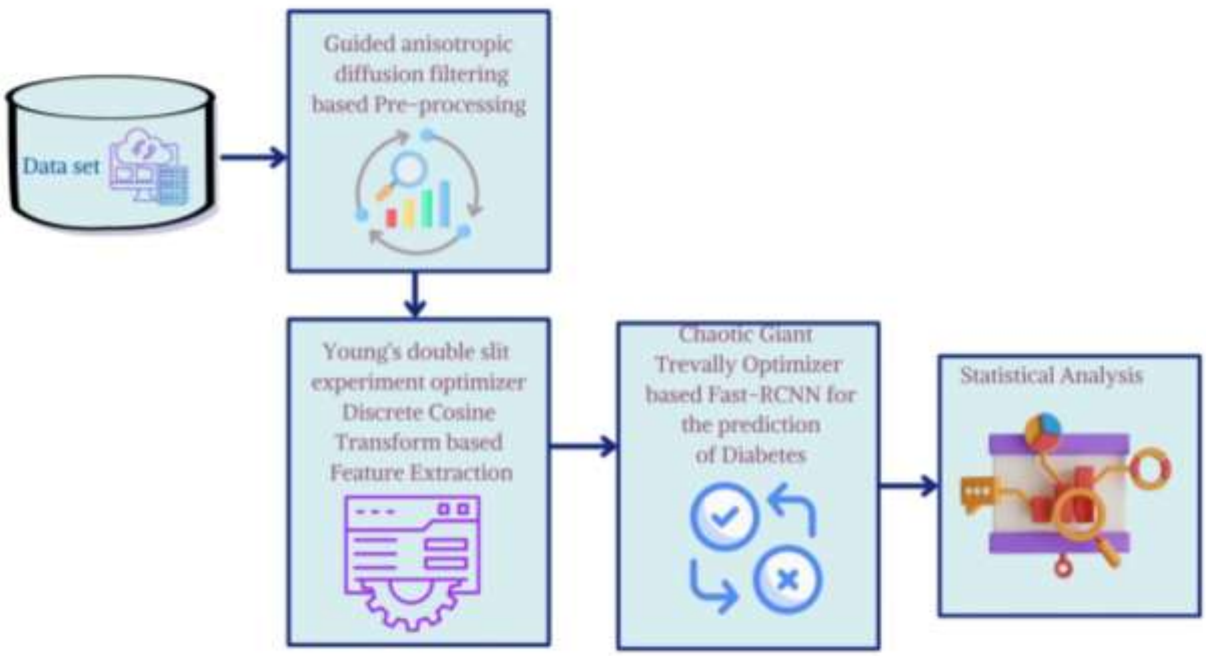


Fig 1: Overall framework for the prediction of risk of diabetes disease in North Kashmir

4.1 Pre-processing of Data

The proposed method is examined and evaluated using clinical dataset. Various kinds of disorders present in clinical dataset. Transform the raw informtaion to the format of data evaalution files to cleaning as well as feature extraction. Cleaning of data in the major step and we used Guided anisotropic difusion filtering (GADF) to data cleansing [17]. Where, the local data is lower and the diffusion coeeficient is higher and the below formula explains anisotropic difusion.

$$\frac{\partial D}{\partial t} = div\big(C(y,z,t)\nabla D\big) \qquad (1)$$

From this equtaion, the input data is D and gradient function is ∇. At time t and position (y,z), the diffusion coefficient is $C(y,z,t)$. The GADF neglects the irrelevant and duplicate data.

After data cleasing, data balancing also has major importance for prediction. In this stage, the remove and hadle the incorrect data to demonstrate accurate and precise findings. Here, we deterimines the missing values like test result, Gender Glucose, Blood Pressure, Skin Thickness, Insulin, BMI, Smoking, Function of Diabetes Pedigree and Patient-number Age. These not contains null values beacause, assigned these parameteers with blank values. Hence, we balance all values by dataset scaling [18]. Combine the data removed from every group maximum of the classifier for instance. Then apply, both over and down samplings.

Random under sampler model correcting the inconsistency with datasets. To every target group, randomly select data as well as every target data groups. The random sample selction with or without modification to vvalidate the number of class. The fresh minority sample size is developed to handle partiality issue. New minority samples to neglect the original one. Several similarities present in both opposing group pair and tomek link. For minority, false data is obtained via synthetic minority oversample method.

4.2 Feature Extraction Model

The features to be extracted for the prediction of disease is explained in section and for that this work utilizes DCT based YDO approach. The YDO enhances the DCT to balance the features with lower and higher frequency components. The detailed version is explained in the following section.

4.2.1 Discrete Cosine Transform

DCT is most commonly used approach for the extraction of features from the various types of data. DCT [22] is an approach used for the oscillation of various frequencies with the sum of cosine functions. Since we have used the patient data we have taken the 1D DCT and its respective coefficients are evaluated as given below,

$$H(u) = \sqrt{\frac{2}{N}}\,\delta(u)\sum_{a=0}^{N-1} h(a) * \cos\left(\frac{\Pi u(2a+1)}{2N}\right) \qquad (2)$$

$$u = 0,1,.....,N-1$$

Meanwhile the definition for the $\delta(u)$ given as,

$$\delta(u) = \begin{cases} \frac{1}{\sqrt{2}} & u = 0 \\ 1 & otherwise \end{cases} \qquad (3)$$

The 1D input vectors incorporated with N number of data values is $h(a)$ and the 1D DCT coefficient vector is $H(u)$ with N number of values. Since the DCT coefficients are both low-frequency components we have used Young's double slit experiment optimizer (YDO) to separate both the components. It is elucidated in the following section.

4.2.2 Young's double slit experiment optimizer for Enhancement of DCT for feature extraction

After the pre-processing the balanced data are forwarded to the YDO-DCT for extracting required features for the risk prediction of diabetes from the data that are collected from the North Kashmir. YDO [23] is based on the young's double slit experiment and the initialization process is explained below.

- **Initialization**

Like the monochromatic light waves (L) passed to the barrier with the slits that are arranged closely, the components with low and high frequency data are placed. The initialization is made from the search space like the L from NP waves as formulated below,

$$L_{i,j} = CL_j + ran \times \left(CU_j - CL_j\right) \qquad (4)$$

Here, $i = 1,2,3,.....,NP$
$j = 1,2,3,.....,D$

The monochromatic wave with ith position and jth variable is $L_{i,j}$. The lower and upper constraints of the NP waves is taken as CL_j and CU_j respectively. the random integer value of ran ranges from 0 to 1 and D is the dimensionality of the problem.

- **Huygens' Principle**

After the completion of projecting through the two slits (two frequency components) the features are spread to all direction based on the principle of Huygens'. Let us assume the number of features forwarded from the first and second slits is almost same as the NP waves and the feature points are evaluated using the following eqns.

$$FL_i = L_i + K \times ran1(-1,1) \times \left(L_{Mean} - L_i\right), \quad i = 1,2,3,....,NP \tag{5}$$

$$SL_i = L_i - K \times ran2(-1,1) \times \left(L_{Mean} - L_i\right), \quad i = 1,2,3,....,NP \tag{6}$$

The first and second feature points are FL_i and SL_i respectively and the mean value of current population of L is L_{Mean} with the best population individual as L_{best}.

- **Traveling waves and path difference update**

The mathematical illustration of two interfering waves and following the path is formulated as,

$$A_i = \left(\frac{FL_i + SL_i}{2}\right) + \Delta K \tag{7}$$

The path difference between the two points of features is measured as ΔK

- **Wave amplitude update**

It can be effectively formualted as follows,

$$P_B^{t+1} = \frac{2}{1 + \sqrt{\left|1 - \alpha^2\right|}} \tag{8}$$

The average amplitude of wave when it is bright fringe is P_B^{t+1}. Meanwhile, when two waves superimpose then it will explicitly becomes low amplitude and can be mathematically illustrated as,

$$P_D^{t+1} = \rho \times \tanh^{-1}\left(\frac{-t}{T} + 1\right) \tag{9}$$

The constant ρ =0.39.

- **Exploration Stage**

To avoid falling for loacloptima the location up-gradation can be formulated as follows,

$$Int_{m_{odd}}^{t+1} = Int_{\max}^{t+1} \times \cos^2\left(\frac{\Pi d}{\sigma K} b_{dark}^{t+1}\right) \tag{10}$$

The interval between the central fringe b_{dark}^{t+1} and the dark fringe m_{odd}^{th} can be given as $Int_{m_{odd}}^{t+1}$.The trail vector in size D can be given as,

$$Q = \frac{x}{F} \tag{11}$$

- **Exploitation Stage**

Mathematically the exploitation stage is expressed as,

$$Int_{m_{even}}^{t+1} = Int_{\max}^{t+1} \times \cos^2\left(\frac{\Pi d}{\sigma K} b_B^{t+1}\right) \tag{12}$$

The interval between the central fringe and bright fringe m_{even}^{th} is given as b_B^{t+1}. The location up-gradation is performed as,

$$A_{m_{zero}}^{t+1} = A_{best}^{t} + \left(P_B^{t+1} \times Int_{\max}^{t+1} \times A_{m_{zero}}^{t} - c_3 \times q \times A_{rb}^{t}\right) \tag{13}$$

$$Int_{\max}^{t+1} = E \times z \tag{14}$$

$$z = \frac{t}{T} \tag{15}$$

the update part of YDO is formulated as,

$$A_m^{t+1} = \begin{cases} A_{best}^{t} + \left(P_B^{t+1} \times Int_{\max}^{t+1} \times A_m^{t} - c_3 \times q \times A_{rb}^{t}\right) & if \quad m = 0 \\ A_m^{t} - \left((1-s) \times P_B^{t+1} \times Int_m^{t+1} \times A_m^{t} + s \times B\right) & if\ m\, is\, even \\ A_m^{t} - \left(c1 \times P_{dark}^{t+1} \times Int_m^{t+1} \times A_m^{t} - Q \times A_{best}^{t}\right) & if\ \ m\, is\, odd \end{cases} \tag{16}$$

The pseudocode for the YDO is listed in Algorithm 1.

Algorithm 1: Pseudocode of YDO used for improving the feature extraction quality of DCT from low and high frequency components

Initialize the inputs, outputs,
Initialize monochromatic source of light waves (4)
The outgoing waveforms are created using eqns. (8) and (9)
Create the population A of NP and update location using eqn. (10)
The constraints of fringes are verified
Estimate the fitness of the fringes/solutions
Separate the A_{best} which has minimum fitness value
Arrange the solution
The maximum intensity of the solution is defined in the central region
Determine the current iteration t=1
Arrange the fringes from best to worst based on the fitness and location upgradation
for m=0:NP-1
Update the value of q using (11)
If(m=0)
Upgrade the central fringe intensity using eqn. (14)
Upgrade the central fringe amplitude using eqn. (8)
Upgrade the central fringe using the eqn. (16)
Else if(m=even number)
The intensity of the bright fringe is updated using eqn. (17)
The amplitude of the bright fringe is updated using the eqn. (7)
The second state of the bright fringe is updated using eqn. (18)
Else
The intensity of the dark fringe is updated using eqn.(10)
The amplitude of the dark fringe is updated using eqn. (11)
The third state of the dark fringe is updated using eqn. (12)
End
Verify the constraints of each fringe
End for
Increase the iteration to next level
End while

4.3 Prediction Model

This is the section to explain the techniques used for the prediction of risk of diabetes disease in a wider context. This section includes the details about Faster RCNN followed by YDO algorithm, and the proposed prediction model.

4.3.1 Faster RCNN

Faster R-CNN [24] is the best deep learning approach used for the prediction of diseases, patterns with high accuracy. Hence we adopted it for the risk prediction of diabetes in the north Kashmir area. The proposed Faster RCNN is the enhanced version of the conventional Fast RCNN and it is employed with region proposal network (RPN) and distributed feature map, nevertheless, in traditional one edge box strategy and selective search algorithm. This explicitly increases the operational efficacy, training speed with the mitigation of computational complexities. It consists of various layers such as feature extractor layer known as backbone, RPN, RoI pooling, and prediction layer.

- **Feature selector (Backbone)**

This layer is used to select the kinematic and spatiotemporal features from the features that are extracted by the proposed YDO-DCT and produce feature maps. It is made up of many layers known as convolution and pooling layers. in this work Visual geometry group (VGG) is used ought to the significance of converting the unstructured data into higher dimensional vectors.

- **RPN layer:**

The main purpose of this layer is generating anchors for the processed data from the backbone layer. the generated anchors are processed using the binary classifier and bounding box regression. The usage of these two operations are the binary classifier monitors the location of the target and placed within the anchor and bounding box regressing is utilized to generate the regression by altering the coordinates of anchor.

- **RoI pooling Layer**

The mapped features are undergo pooling estimator to transform the various dimensioned feature maps to the same dimensionality feature maps and used by the fully connected layer to acquired the required prediction output.

The feature proposals of RPN are different from the fully connected layer i.e, non-uniform in structure. The feature maps are scanned positioned further with the sliding window of size N×N, and anchors of ω in distributed anchor. Each anchor provided four regression factors along with 2 prediction scores

The resultant anchor can be computed with ignoring the anchors from the outside of the targeted constraints. The loss function of RPN after eliminating the anchors outside the constraints is measured with randomly choosing the number r. the anchor is considered as positive when the IoU (intersection over union) is greater than 0.7 value of ground truth and below 0.3 ground truth are considered as negative. Mathematically, the RPN loss function is described as,

$$\psi\left(\{\vartheta_x\},\{\tau_x\}\right)=\frac{1}{t_c}\sum_x \psi_c\left(\vartheta_x,\vartheta_x^*\right)+\eta\frac{1}{t_R}\psi_R\left(\tau_x,\tau_x^*\right) \quad (17)$$

The weighting factor of the xth anchor is ψ . The error rate ψ_c that are evaluated from the difference between the predicted anchor box and xth ground truth anchor shown in the above figure can be done utilizing the softmax cross entropy. The probability prediction at foreground of xth anchor is ϑ_x and the ground truth value that indicated negative and positive is indicated as ϑ_x^*.

$$\psi_c=-\left[\vartheta_x^*\log(\vartheta_x)+\left(1-\vartheta_x^*\right)\log\left(1-\vartheta_x\right)\right] \quad (18)$$

The smooth function is utilized along with the regression loss ψ_R to evaluate the error of target location. The regression box detected by xth anchor is τ_x and the absolute value of regression box parameter is τ_x^* and the predicted output can be defined as,

$$\psi_R\left(\tau_x, \tau_x^*\right) = \sum_x smooth_{G1}\left(\tau_x, \tau_x^*\right) \tag{19}$$

$$smooth_{G1}(O) = \begin{cases} 0.5O^2, & |O| < 1 \\ |O|, & else \end{cases} \tag{20}$$

4.3.2 Chaotic Giant Trevally Optimizer (CGTO)

In jack family, large marine predator us giant trevally (GT), which is also named as giant kingfish that widely determined in East Africa. Few dark spots with silver in colour giant trevally. Daily it consumes seabirds, crustaceans, cephalopodan and fishes. In the Indian Ocean, remote atolls over half million terns crowd during the season of dry [19]. GT initiate to prey chasing and it jumps out of water then prey attacking after specifying the area of hunting. Giant trevally optimizer (GTO) inspires the principle of giant trevally (GT). Further, the chaotic map of chaotic map (Kent map) for wide search in GTO algorithm and it is named as Chaotic Giant Trevally Optimizer (CGTO).

3.2.1 Initializing solution:

The GT randomly initializing the solutions similar to other population oriented meta-heuristic algorithms. To solve optimization issue, the candidate solution possible to every giant trevally in GTO. The algorithm population matrix constituted vectors and vector is the population of every member. Equation (1) updates the member population of GTO.

$$Z = \begin{bmatrix} Z_1 \\ \vdots \\ Z_j \\ \vdots \\ Z_M \end{bmatrix}_{M\times \dim} = \begin{bmatrix} z_1 & \cdots & z_{1,j} & \cdots & z_{1,\dim} \\ \vdots & \ddots & \vdots & \iddots & \vdots \\ z_{k,1} & \cdots & z_{j,k} & \cdots & z_{j,\dim} \\ \vdots & \iddots & \vdots & \ddots & \vdots \\ z_{M,1} & \cdots & z_{M,D} & \cdots & z_{M,\dim} \end{bmatrix}_{M\times \dim} \tag{21}$$

The GTO j[th] candidate solution is Z_j with the candidate solution is Z. The decision variable dimension is dim and the GTO members are M. The j[th] candidate solution specifies the k[th] variables $z_{j,k}$. In $M \times \dim$ search space, all possible regions should be covered via random assignment and it is expressed as,

$$z_{j,k} = \min_k + \left(\max_k - \min_k\right) \times P \tag{22}$$

Here, the random number P to the interval [0, 1] and $k = 1,2,\ldots,\dim$ with $j = 1,2,\ldots,M$. The maximum and minimum population based on k[th] dimension is $\max_k$ and $\min_k$ [20]. Each solution candidates assess the objective function and the values are represented using vector and expressed as,

$$OF = \begin{bmatrix} OF_1 \\ \vdots \\ OF_j \\ \vdots \\ OF_M \end{bmatrix}_{M\times 1} = \begin{bmatrix} OF\left(Z_1\right) \\ \vdots \\ OF\left(Z_j\right) \\ \vdots \\ OF\left(Z_M\right) \end{bmatrix}_{M\times 1} \tag{23}$$

The objective function vector (OF) with j[th] member value is OF_j.

3.1.2 Mathematical modelling:

During seabirds hunting, the GT mimics the GTO algorithm. It includes few major stages namely; chaotic map (Kent map) for wide search, hunting area determination using area selection, prey chasing and attacking. The prey chasing and attacking phase includes exploitation stage and the remaining stages includes exploration.

❖ **Wide search**

For daily diet, GT travels to longer distances. Below expression simulates the GT foraging movement.

$$Z(T+1) = P \times P_{best} + \left(\left(Max - Min\right) \times P + Min\right) \times \text{chaotic map (dim)} \tag{24}$$

Position vector of GT's next iteration is $Z(T+1)$. During last search, determine the best position based on GT select current search space is P_{best}. The chaotic movement generates the ability to simple system is one dimensional chaotic maps [21]. From eight different chaotic maps, we select Kent map are selected to enhance the wide search performance of GT since chaotic map has better rate of convergence and local optimal avoidance. The Kent of chaotic map is illustrated as,

$$Z_{m+1} = \begin{cases} \dfrac{Z_m}{\alpha}, & 0 \le Z_m \le \alpha \\ \dfrac{(1-Z_m)}{(1-\alpha)}, & \alpha < Z_m \le 1 \end{cases} \tag{25}$$

The control parameter and chaotic variable are α and Z_m.

❖ **Area selection**

Within the selected search space, the best area is selected and identifying GT in area selection step. To hunt prey, the search space is selected.

$$Z(T+1) = P \times P_{best} \times \beta + Info_{mean} - Z_j(T) \times P \tag{26}$$

To next generation, the GT position vector is $Z(T+1)$ with the controlling parameter to position variation is β. At time T, the GT location is $Z_j(T)$ with the mean is referred as $Info_{mean}$.

$$Info_{mean} = \frac{1}{M}\sum_{j=1}^{M} Z_j(T) \tag{27}$$

❖ **Attacking of prey**

For hunting, best area is specified with previous steps. GT close near the bird and it attack the bird. Below expression outlines the Snell law,

$$\delta_1 \sin\theta_1 = \delta_2 \sin\theta_2 \tag{28}$$

The angle of incidences is θ_1 and θ_2 with the visual distortion (μ) and distance is evaluated as,

$$\sin\theta_1 = \frac{\delta_2}{\delta_1}\sin\theta_2 \tag{29}$$

$$\mu = \sin\left(\theta_1^o\right) \times dis \tag{30}$$

$$dis = \left|P_{best} - Z_j(T)\right| \tag{31}$$

The prey location represented with the best achieved solution P_{best} consequently far. While chase and jump out of water, the mathematical model of GT behaviour is as,

$$Z(T+1) = \psi + \mu + \lambda \tag{32}$$

At current iteration T, the birds chasing speed is represented as ψ and the fitness function $OF\left(Z_j(T)\right)$.

$$\psi = Z_j(T) \times \sin\left(\theta_1^o\right) \times OF\left(Z_j(T)\right) \qquad (33)$$

From the exploration to exploitation stage, GT enables the jumping slope (λ) and explained as,

$$\lambda = r \times \left(2 - T \times \frac{2}{t}\right) \qquad (34)$$

Where, the random number is r and both maximum as well as current iteration is t and T. During the stage of exploitation, the neighborhood or best solution is exploited. Figure 2 represent the flowchart of CGTO algorithm.

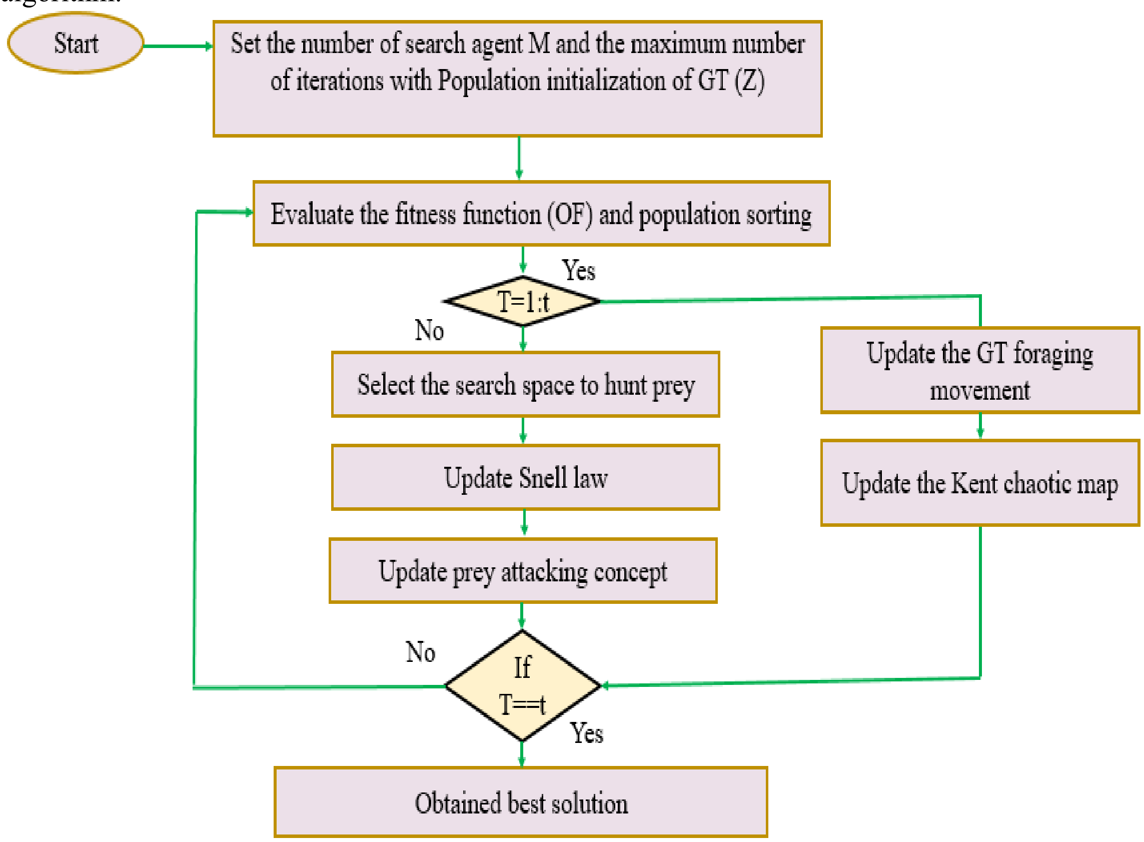


Fig 2: CGTO algorithm flowchart

4.3.3 Proposed CGTO based hyperparameter tuned Faster RCNN for the risk prediction of diabetes in north Kashmir

The proposed Faster RCNN is failed to provide maximun prediction rate with the default learning of hyperpaarmeters. To analyze the spatiotemporal features and kinematic features with the perfect combination of parameter values it is essential to tune the hyperparameters in a right way. For that we have utilized CGTO algorithm to attain global prediction value. The best values are predicted using the proposed CGTO algorithm using various algorithm.The next step is to estimate the fitness function to evaluate the predicted performance of proposed CGTO-Faster RCNN predictor and can be interpreted as,

$$Fitness\ Function = \Pr ediction\ Error = \frac{No.of\ wrongly\ predicted\ data}{Total\ No.of\ data} \qquad (35)$$

The risk prediction of diabetes disease among north Kashmir can be trained and analyzed using the proposed CGTO-Faster RCNN thus ensures maximum prediction accuracy and the schematic overlay of proposed approach is depicted in figure 3.

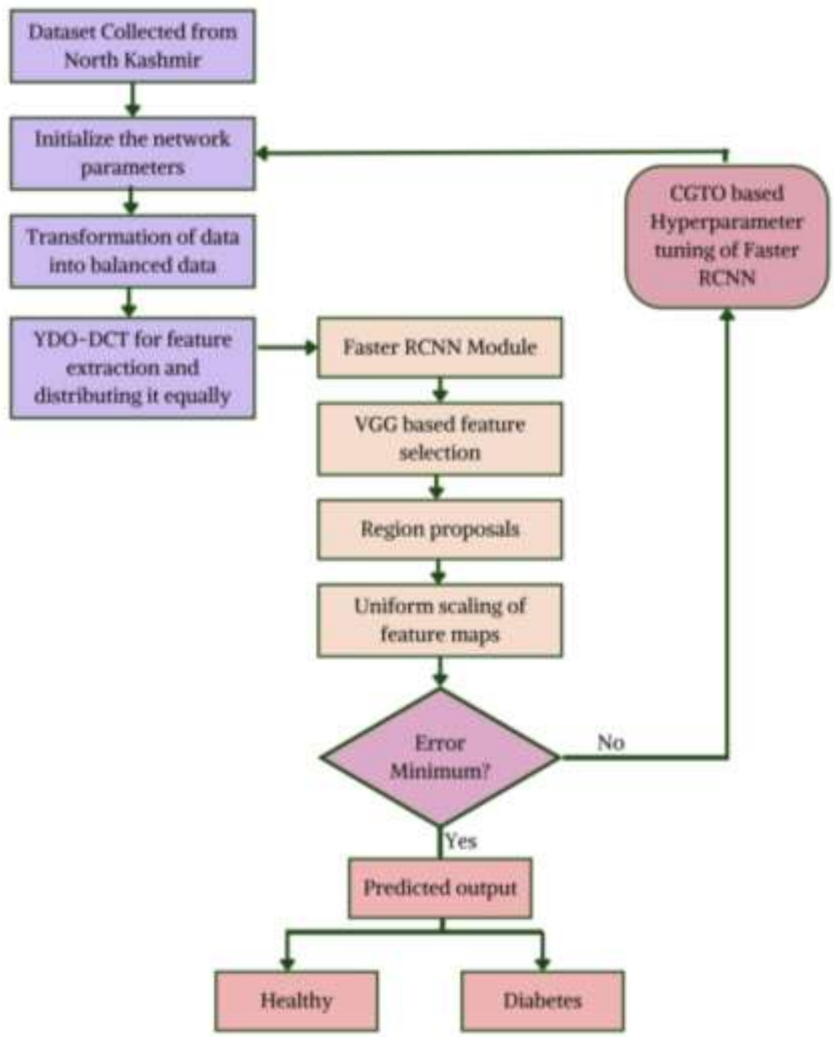


Fig 3: Proposed Schematic overlay of prediction of risk factors of diabetes

5. Experimental Result and Discussion:

The proposed framework effectiveness is evaluated in this section. The Intel Core (TM) i5-8400 CPU@2.8GhZ equips with the software environment python handles the implementation part. By this, the proposed diabetic prediction performance evaluation as well as state-of-art study conducted with respect to evaluation parameters. Table 3 explains the parameter description.

Table 3: Parameter illustration

Parameters	Ranges
Population size	100
Number of epochs	300
μ	0.4
ψ	2
Batch size	256

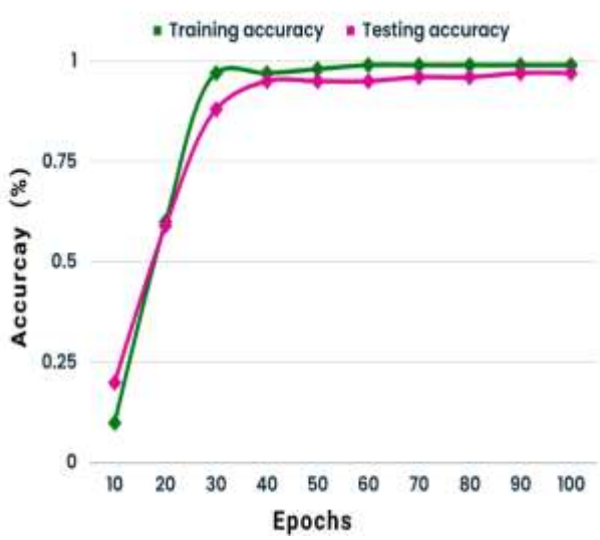
Decay learning rate	0.00001
Weight decay	0.00004

5.1 Evaluating proposed method performance:

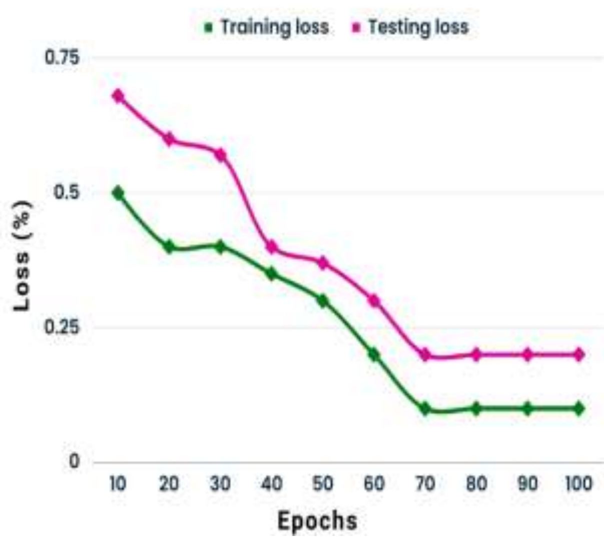
The model performance measure efficiency is checked using K-fold cross validation model. The set of training model to check the performance by preparing original dataset. Divide the entire data item and K-indicates the number of sections. Several iterations conducts the experiment to get the statistical reliable results. Conduct the iteration in 10 if the K-value is 10. Training set select the remaining K-1 sections also the test set choose K-one section of each value out of K-iteration. Equal possibility of test set is acquired as the benefit of using cross fold validation in each section. The diabetic prediction model's performance measures shown after K-experiments to take the mean of obtained results. After K-experiment, equation (35) gives the calculated mean of attained results and the accuracy is mentioned in equation (36).

$$Accuracy = \frac{No.of\ correctly\ predicted\ \ data}{Total\ No.of\ data} \qquad (36)$$

The training and testing accuracy performance of proposed method is oulined in Figure 4. There are 10 to 100 itterations takes to check both accuracy and loss as shown in Figure 4 (i) and 4 (ii). The epochs increases with increasing both training and testing accurcay. As well as, the training and testing loss decrases with increasing the number of epochs. By the evlaution of this plot, the proposed method ouutperformeed increased tarining accuracy and minimized training loss.



(i)



(ii)

Fig 4: Performance of proposed work based on (i) training and testing accuracy and (ii) training and testing loss

Figure 5 illustrates the assessment based on the prediction loss. The prediction loss decreases with the number of epoch's increases and the loss is low for our approach with the utilization YDO based Faster RCNN. The prediction loss at epoch 150 is 6.09% and at 300th epoch the prediction loss is 2.11%.

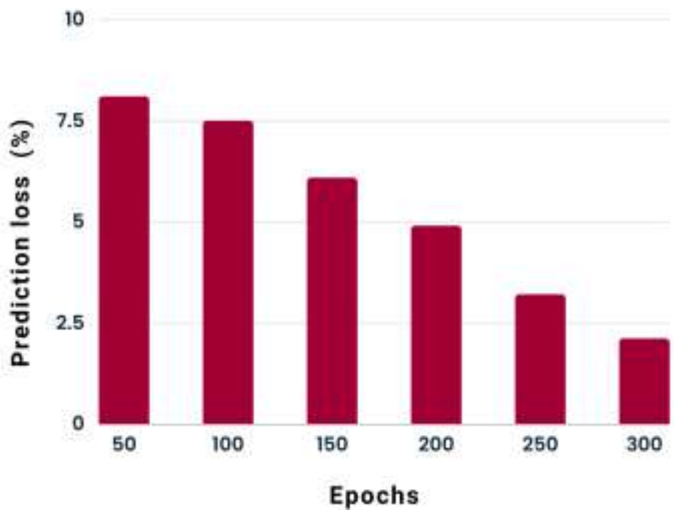


Fig 5: Assessment based on prediction loss

The assessment based on the memory usage for varying epoch is shown in figure 6. The memory usage is lower at 50th epoch and higher at 300th epoch. The memory usage changed with respct to the number of epochs. At 100th epoch the memory usage is 25.8KB and 300th epoch the memory usage is 175 KB and is lower than many of the state-of-art works.

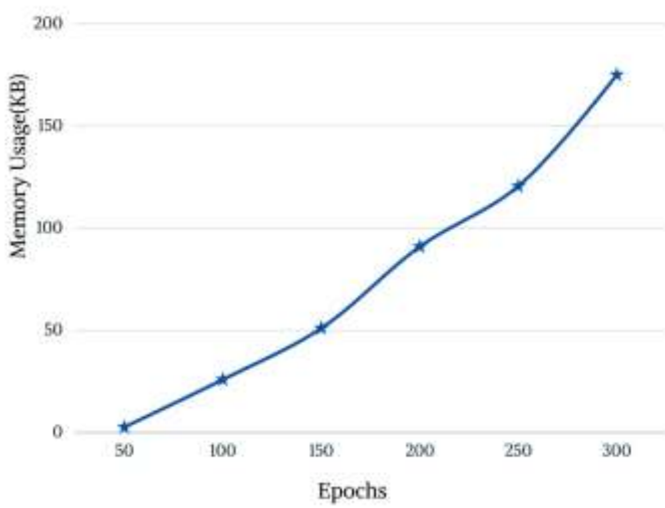


Fig 6: Assessment based on memory usage

For the assessment of proposed work we have taken three parameters such as prediction loss, training speed, and memory usage for over 300 epochs using the 1023 instances and 8 attributes. Figure 7 illustrates the training speed in percentage for the epochs 50 to 300. The training speed of proposed approach increases with the epochs and at epoch 50 the training speed is 0.000045 s and at 300th epoch the training speed is 0.178 s.

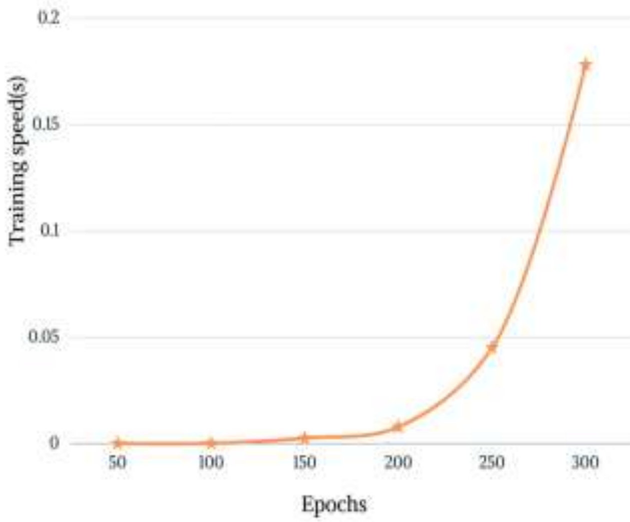


Fig 7: Assessment based on training speed

4.2 Evaluating state-of-art techniques performance:

Figure 8 shows the comparative study of accuracy with respect to existing methods namely HPTI-v4 [9], DCNN [10], ML [13], and DLPD [15] with proposed method. This graph is plotted and varied based on the number of epochs as 300. From 50 to 300 epochs, the proposed system prove the prediction accuracy of 95%, 95.8%, 95.9%, 96%, 96.2% and 97.3% separately. We found that the prediction accuracy of proposed is higher. At 300th epochs, we have got 82%, 93%, 85%, 91% and 97.3% by means of HPTI-v4 [9], DCNN [10], ML [13], DLPD [15] and proposed method. Rather than other existing methods, the proposed diabetic prediction model beats higher accuracy.

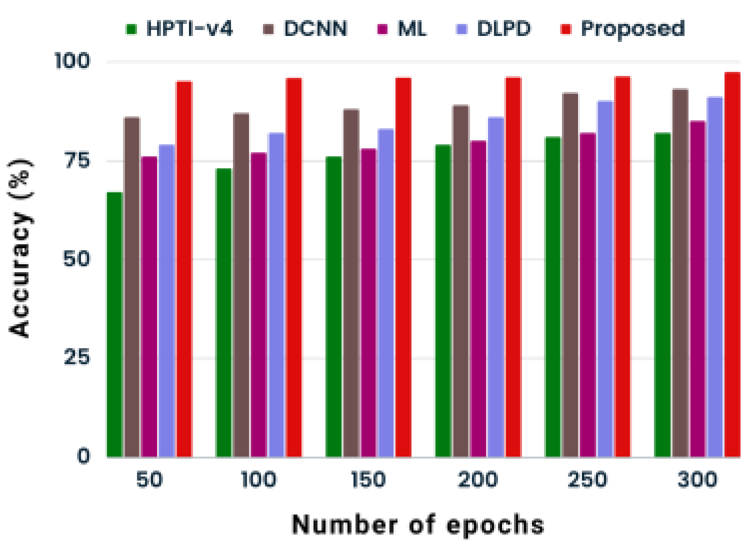


Fig 8: State-of-art evaluation of accuracy

The state-of-art study of specificity for diabetic prediction is plotted in Figure 9. The methods namely proposed method with HPTI-v4 [9], DCNN [10], ML [13], and DLPD [15] approaches discloses the ability of specificity by varying 300 epochs. The specificity of 95%, 95.4%, 95.8%, 96%, 96.9% and 97.2% are achieved by varying the number of epochs from 50 to 300. There is greater specificity during diabetic prediction is succeeded. The proposed methods with existing approaches exhibits 81%, 92%, 86%, 93% and 97.2% at 300th epochs. Nevertheless, higher specificity result is accomplished rather than other previous techniques.

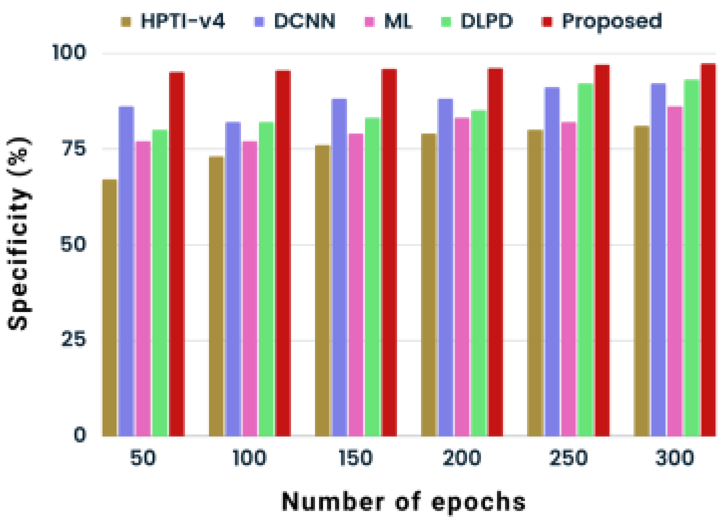


Fig 9: State-of-art evaluation of specificity

Figure 10 plot the comparative reading of sensitivity based on the existing procedures specifically HPTI-v4 [9], DCNN [10], ML [13], and DLPD [15] with proposed technique. This graphical representation is designed and wide-ranging depending upon a number of epochs is from 50 to 300. At these epochs, the diabetic prediction sensitivity of proposed scheme evidences that 95.3%, 95.6%, 95.8%, 96.1%, 96.3% and 97% sensitivity. This graphical plot originate that the proposed diabetic prediction sensitivity is sophisticated. At the level of 300th epochs, the 82%, 93%, 88%, 94% and 97% is got with respect to the techniques namely HPTI-v4 [9], DCNN [10], ML [13], DLPD [15] and proposed method. Reasonably to further existing approaches, the proposed diabetic prediction model offer higher sensitivity outputs.

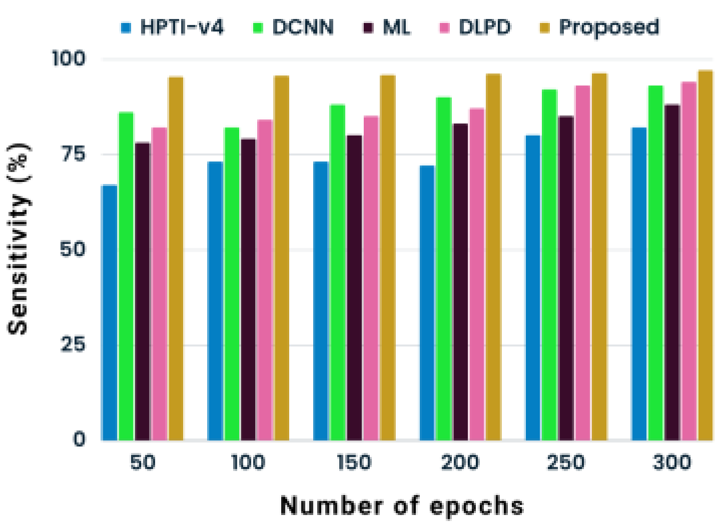


Fig 10: State-of-art evaluation of sensitivity

Figure 11 reveals the comparison plot for overall efficiency for diabetic prediction. This bar diagram sketch overall efficiency of 65%, 90%, 88%, 92% and 97% in terms of HPTI-v4 [9], DCNN [10], ML [13], DLPD [15] and proposed method. The graphical representation discloses higher rate of efficiency rather than other existing methods like HPTI-v4 [9], DCNN [10], ML [13] and DLPD [15].

Fig 11: Overall efficiency based on comparison plot

6. Conclusion

In this article, the work is proposed to predict the risk of diabetes disease among north Kashmir. For the study we have taken 1023 instances with 8 attributes. The data collected were pre-processed to remove the null sets and converting the imbalanced data into balanced data using the GADF approach which effectively pre-processed the data for further processing. For feature extraction we have utilized the YDO-DCT approach and extracted the required features. Henceforth, the extracted features were selected using the Backbone layer of Faster RCNN technique for the mapping. The selected features were used for the prediction disease using the proposed CGTO-Faster RCNN and predicted as Healthy and Diabetes. The prediction loss of proposed approach at 300th epoch is 2.11% and thus improves the prediction accuracy. By compared to the previous methods namely HPTI-v4, DCNN, ML and DLPD, we have gained 97.3% accuracy, 97.2% specificity and 97% sensitivity.

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