Big Data predictive analysis for type-2 diabetes based heart disease using feature extraction and classification by machine learning architectures

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Abstract: Machine learning (ML), a branch of AI, enables computers to learn without being explicitly programmed. ML is widely applied in the healthcare industry to forecast a variety of chronic conditions. For improved clinical paths to prevent complications and postpone the onset of diabetes, earlier diabetes prediction is essential. This research propose novel technique in type 2 diabetes based heart disease detection in big data predictive analysis using machine learning technique. here the input data has been collected as type 2 diabetes and processed for noise removal and dimensionality reduction. Then the processed data features has been extracted for detecting the abnormality of type 2 diabetes using regression model based linear discriminant analysis. The extracted features shows the abnormal type 2 diabetes and for predicting heart disease by classifying the extracted data using VGG-16 Net_gradient neural network. the experimental analysis has been carried out in terms of accuracy, precision, recall, F-1 score, RMSE and MAP for various diabetes dataset. Proposed technique attained accuracy of 96%, precision of 67%, recall of 79%, F-1 score of 63%, RMSE of 66% and MAP of 68%.

Keywords: *Machine Learning, big data, predictive analysis, type 2 diabetes, dimensionality reduction*

1. Introduction

Diabetes is a disease that develops when your blood glucose level is higher. The primary and first source of blood glucose is provided by the food you eat. In particular, a substance produced by the digestive system allows different sugars from food to enter your cells and be used as an energy source [1]. Sometimes a corpse doesn't use offence well, doesn't cause enough uproar, or both. Sometimes people refer to this condition as "borderline diabetes" or "a touch of sugar." These circumstances suggest that someone may not actually have diabetes or may have a milder disease, although each instance of the ailment is dangerous. Type 1, type 2, and developing diabetes are three most common types of diseases. At that time, the sugar energy supply is still in your blood and has not reached your basic unit of a living thing. HD refers to a wide range of illnesses that affect your heart. Term "heart disease" refers to a variety of infections, including blood vessel diseases including coronary artery infection, arrhythmias, and inherited heart defects (innate heart surrenders) [2]. Machine learning can be crucial in predicting the presence or absence of diabetes, heart infections, locomotor disorders, and more. Such information, if predicted well in advance, can provide professionals with critical information that will allow them to modify their therapy and decision-making for each patient. The most common life-threatening illness is diabetes. About 1.5 million people died from diabetes-related causes in 2012, and heart disease, renal issues, and other causes of death accounted for another 2.2 million deaths. About 8.8% of people worldwide had diabetes mellitus as of 2017. By 2045, it is anticipated to reach 10%[3]. About 77 million Indians have high blood sugar, placing the country in second place for the number of diabetic patients worldwide (Saeedi et al., 2019). The National Diabetes Statistics Report 2020 estimates that around 34.2 million Americans have high blood sugar. Only 26.9 million people in the population have been diagnosed with diabetes, and the remaining 7.3 million are unaware that they have the disease (US Department of Health and Human Services, 2020). Diabetes can be diagnosed manually by a doctor or automatically using a gadget. Both diagnostic techniques have benefits and drawbacks. The biggest advantage of performing diagnoses manually is that an automatic instrument is not required [4].

Contribution of this research is as follows:

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1. To propose novel method in type 2 diabetes based heart disease detection in big data predictive analysis using machine learning technique
2. the processed data features has been extracted for detecting the abnormality of type 2 diabetes using regression model based linear discriminant analysis.
3. The extracted features shows the abnormal type 2 diabetes and for predicting heart disease by classifying the extracted data using VGG-16 Net_gradient neural network.

2. Literature review

Heart and diabetes issues have historically been the two most common causes of death worldwide. Furthermore, it is a problem that requires a solution today to predict the same thing or simply to suggest a slight chance of it. Machine learning has paved its role in the medical industry by assisting in decision-making and forecasting by training over vast amounts of data that already exist in the form of datasets. According to the study in [5], cardiovascular disorders are substantially correlated with the severity and mortality of COVID-19, but diabetes mellitus and hypertension are only weakly related. According to [6], the research focuses on the application of neural network technology to analyse and demonstrate more accurate diabetes prediction. Early decision is possible using a reasonably sound computational method, as stated by [7]. In this study, diabetes is predicted early on using machine learning techniques. This section discusses a few works that are very closely connected. For the purpose of predicting diabetes, many research papers have made use of the Pima Indians Diabetes Dataset (PIDD). Weka tool and ML techniques were used by [8]. Researcher methods can be generically categorised into four categories: ML, data mining, hybrid methods, and genetic or NN methods. Deep learning techniques were applied to electrocardiogram (ECG) information in work [9] to detect diabetes. They specifically utilized CNN and LSTM, and subsequently support vector machines were used to extract features. They discovered a very high accuracy of 95.7% as a result. In order to forecast diabetes, author [10] applied 3 ML approaches to PIDD: decision tree (DT), naive based (NB), and support vector machine (SVM). The accuracy of Naive Bayes classifier was determined to be 76.30%. Work [11] used updated kNN and logistic regression data mining approaches to reliably forecast up to 95.42% of a person's probability of getting type 2 diabetes. The adjustment was carried out by empirically choosing the first seed point's value. In order to forecast diabetes, author [10] applied 3 ML approaches to PIDD: decision tree (DT), naive based (NB), and SVM. The accuracy of Naive Bayes classifier was determined to be 76.30%. Work [11] used updated kNN and logistic regression data mining approaches to reliably forecast up to 95.42% of a person's probability of getting type 2 diabetes. The adjustment was carried out by empirically choosing first seed point's value. By running 100 runs and choosing smallest value of "inside cluster sum of squared errors," initial seed point was determined [12]. Among the three methods, DT was discovered to deliver the best results. Work [13] used a hybrid method that first applied genetic algorithm (GA) for feature selection and then RBFNN for classification. They discovered that the hybrid approach outperformed RBFNN on its own [14].

3. System model:

This section discuss novel technique in type 2 diabetes based heart disease detection in big data predictive analysis using machine learning technique. here the input data has been collected as type 2 diabetes and processed for noise removal and dimensionality reduction. Then the processed data features has been extracted for detecting the abnormality of type 2 diabetes using regression model based linear discriminant analysis. The extracted features shows the abnormal type 2 diabetes and for predicting heart disease by classifying the extracted data using VGG-16 Net_gradient neural network. the proposed architecture is shown in figure-1.

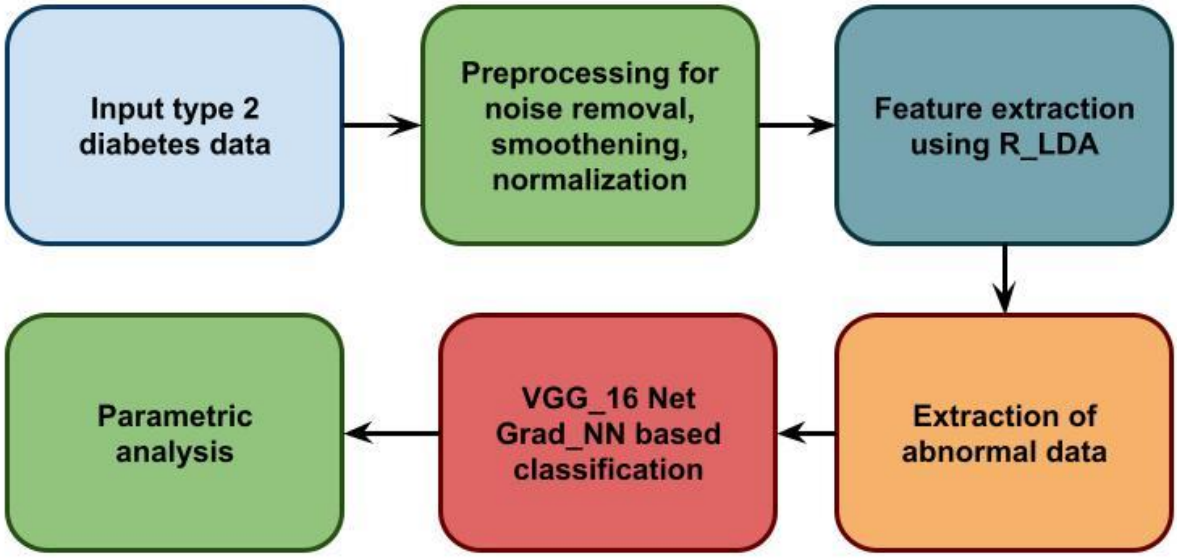

Figure 1: Overall proposed architecture

Data pre-processing is a crucial step to take before developing ML models in order to get better outcomes. The obtained dataset

was preprocessed using several statistical libraries, an Integrated Development Environment called Spyder, and the Python (3.9.1) programming language. Techniques like resampling and discretization were used. Interquartile range approach was used to replace outlier with viable sampling values after the outlier was detected using a boxplot. Before creating the machine learning models, data transformation was done to make the data more effective. Additionally, the dataset has been cleaned of duplicate, inconsistent, and corrupted data utilising a variety of data exploration and analysis approaches.

regression model based linear discriminant analysis

Assume that the data [Y1,Y2,..., Yn] are independent and that Y is a binary response variable with Yi = 1 for the presence of the character and Yi = 0 for the absence of the character. Let I represent the success probability. Additionally, think of the collection of explanatory variables x = (x1, x2,..., xp) as being either discrete, continuous, or a combination of both. The logistic function for I is then provided by equation (1). (2)

$$\text{logit}(\pi_i) = \log\left(\frac{\pi_i}{1-\pi_i}\right) = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{i,pi} \quad (1)$$

where

$$\pi_i = \frac{\exp(\beta_0+\beta_1 x_{i1}+\beta_2 x_{i2}+\cdots+\beta_p x_{i,p})}{1+\exp(\beta_0+\beta_1 x_{i1}+\beta_2 x_{i2}+\cdots+\beta_p x_{i,p})} = \frac{\exp(x_i'\beta)}{1+\exp(x_i'\beta)} = \Lambda(x_i'\beta) \quad (2)$$

Here, I represents the likelihood that a sample falls into a certain category of the dichotomous answer variable, sometimes known as the "success probability," and it is obvious that $0 \le \pi i \le 1$. The logistic cdf is represented by $\Lambda(.)$ where $\lambda(z) = e^2/(1+e^{-z}) = 1/(1+e^{-z})$ and β^s is a vector of parameters that need to be estimated. The odds ratio or relative risk is the expression $\left(\frac{\pi_i}{1-\pi_i}\right)$. Think about the logistic model that uses the logistic function of eq. (3) as the sole predictor variable, X.

$$\pi(X) = \frac{\exp(X_i\beta)}{1+\exp(X_i\beta)} \quad (3)$$

Finding estimates that yield a value near to one for all subjects π(X) who have diabetes and a figure close to zero for everyone else is our goal. The likelihood function is defined mathematically by eq (4)

$$L(\beta_0,\beta_1) = \prod_{i:y_i=1}\pi(x_i)\prod_{r':y_\ell=0}\left(1-\pi(x_{p'})\right) \quad (4)$$

In order to optimise this likelihood function, the estimations are selected. In order to construct and apply the log-likelihood function for estimate, we take the logarithm on both sides. To determine if any subset of estimates β is zero, we employed the likelihood ratio. Assume that p and r stand for the complete model's and the reduced model's respective numbers of βˆ eq(5) outputs the likelihood ratio test statistic

$$\Lambda^* = -2\left[l(\hat{\beta}^{(0)}) - l(\hat{\beta})\right] \quad (5)$$

Therefore, because inner product captures similarity between two vectors, provides a measure of that similarity. We may create a kernel matrix using equation (6) by computing the kernel of two matrices, $\boldsymbol{X}_1 \in \mathbb{R}^{d\times n_1}$and $\boldsymbol{X}_2 \in \mathbb{R}^{d\times n_2}$

$$\mathbb{R}^{n_1\times n_2} \ni \boldsymbol{K}(\boldsymbol{X}_1,\boldsymbol{X}_2) := \boldsymbol{\Phi}(\boldsymbol{X}_1)^\top\boldsymbol{\Phi}(\boldsymbol{X}_2) \quad (6)$$

where $\Phi(\boldsymbol{X}_1) := [\phi(\boldsymbol{x}_1),\ldots,\phi(\boldsymbol{x}_n)] \in \mathbb{R}^{t\times n_1}$ is matrix of mapped X1 to feature space. $\boldsymbol{\Phi}(\boldsymbol{X}_2) \in \mathbb{R}^{t\times n_2}$ is defined. We can evaluate kernel matrix of dataset $\boldsymbol{X} \in \mathbb{R}^{d\times n}$ over itself by eq. (7):

$$\mathbb{R}^{n\times n} \ni \boldsymbol{K}_x := \boldsymbol{K}(\boldsymbol{X},\boldsymbol{X}) = \boldsymbol{\Phi}(\boldsymbol{X})^\top\boldsymbol{\Phi}(\boldsymbol{X}) \quad (7)$$

where Φ(X) := [φ(x1), . . . , φ(xn)] ∈ R t×n is pulled data. d_B in feature space is given by eq. (8):

$$\mathbb{R} \ni d_B := \phi(u)^\top\Phi(S_B)\phi(u) \overset{(a)}{=} \boldsymbol{\theta}^\top\boldsymbol{\Phi}(\boldsymbol{X})^\top\left(\phi(\boldsymbol{\mu}_1)-\phi(\boldsymbol{\mu}_2)\right)\left(\phi(\boldsymbol{\mu}_1)-\phi(\boldsymbol{\mu}_2)\right)^\top\boldsymbol{\Phi}(\boldsymbol{X})\boldsymbol{\theta}, \quad (8)$$

For j-th elass (here $j \in \{1,2\}$), we have by eq. (9):

$$\boldsymbol{\theta}^\top\boldsymbol{\Phi}(\boldsymbol{X})^\top\phi(\boldsymbol{\mu}_j) \overset{(95)}{=} \sum_{i=1}^n\theta_i\phi(\boldsymbol{x}_i)^\top\phi(\boldsymbol{\mu}_j)\left(\phi\left(\boldsymbol{x}_i^{(j)}\right)-\phi(\boldsymbol{\mu}_j)\right)^\top\Big) \overset{(98)}{=} \frac{1}{n_j}\sum_{i=1}^n\sum_{k=1}^{n_j}\theta_i\phi(x_i)^\top\phi\left(x_k^{(j)}\right) \overset{(86)}{=} \sum_{i=1}^n\sum_{k=1}^{n_j}\theta_i k\left(x_i,x_k^{(j)}\right) = \theta^\top m_j \quad (9)$$

dW in feature space is by eq. (10), (11)

$$\mathbb{R} \ni d_W := \phi(\boldsymbol{u})^\top\Phi(\boldsymbol{S}_W)\phi(\boldsymbol{u}) \overset{(\alpha)}{=} \left(\sum_{\ell=1}^n\theta_\ell\phi(\boldsymbol{x}_\ell)^\top\right)\left(\sum_{j=1}^c\sum_{i=1}^{n_j}\left(\phi\left(x_i^{(j)}\right)-\phi(\boldsymbol{\mu}_j)\right)\left(\sum_{k=1}^n\theta_k\phi(\boldsymbol{x}_k)\right)\right) = \sum_{j=1}^c\sum_{\ell=1}^n\sum_{i=1}^{n_j}\sum_{k=1}^n\left(\theta_l\phi(x_\ell)^\top\left(\phi\left(x_i^{(j)}\right)-\phi(p)\right)\right) \quad (10)$$

$$\sum_{j=1}^c\sum_{i=1}^n\sum_{i=1}^c\sum_{i=1}^n\left(\theta_k k\left(x_i,x_i^{()'}\right)-\frac{1}{n}\sum_{i=1}^n\theta_i k\left(\boldsymbol{x}_i,x_i^{(j)}\right)\right)\left(\theta_k k\left(x_k,x_i^{(i)}\right)-\frac{1}{n_j}\sum_{x=1}^n\theta_k k\left(x_k,x_i^{(j)}\right)\right) = \sum_{j=1}^c\sum_{i=1}^n\sum_{i=1}^n\sum_{i=1}^n = \sum_{j=1}^c\left(\sum_{i=1}^n\sum_{i=1}^{n_j}\sum_{k=1}^n\left(\theta_t\theta_k k\left(x_t,x_i^{(j)}\right)k\left(x_k,x_i^{(j)}\right)\right)\right) + \frac{\theta_i\theta_k}{n_j^\top}\sum_{k=1}^{n=1}\sum_{i=1}^{nj\left(x_t,x_i^{(j)}\right)k\left(x_k,x_i^{(j)}\right)}\Big) \overset{(e)}{=} \sum_{j=1}^c\left(\theta^\top K_j K_j^\top\theta - \theta^\top K_j\frac{1}{n_j}11^\top K_j^\top\theta\right) \quad (11)$$

VGG-16 Net_gradient neural network:

The pooling layers in VGG-16 are all 2×2 pooling layers with a stride size of 2, while the convolutional layers are all 3×3 convolutional layers with a stride size of 1 with the same padding. The VGG-16 input image size is 224×224 by default. The size of the feature map is halved after each pooling layer. The 7×7 with 512 channels feature map, which is enlarged into a vector with 25,088 (7×7×512) channels, is final feature map before completely connected layers. In order to assure correctness of model feature extraction as well as to realise model's lightweight and accelerate training, we will merge the original VGG-16 with the full convolution model and minimise the model's parameters as well as the number of layers of the complete connection layer. Our model combines the conventional full CNN model with the original VGG-16 model.

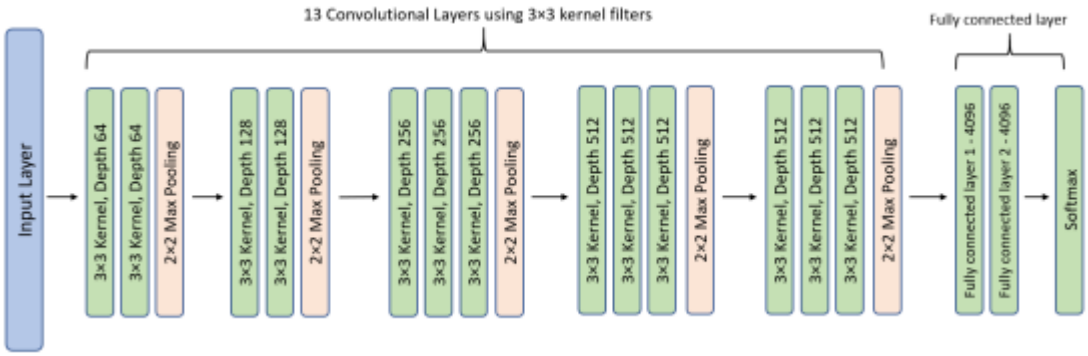

Fig. 2. VGG-16 model architecture – 13 convolutional layers and 2 Fully connected layers and 1 SoftMax classifier

VGG-16 - In their 2014 publication, "Very Deep Convolutional Network for Large Scale Image Recognition," Karen Simonyan and Andrew Zisserman introduced VGG-16 architecture.

$$R^{m,j} = \Delta \mathbf{u}^{m/+j} - \Delta_j \mathbf{u}^{mJ}$$
$$r_i^{m,j} = \Delta_j v_i^{m/j+j} - \Delta_j v_i^{mj}$$
$$d^{m,I} = \mathbf{u}^{\mathrm{m}/+1} - \mathbf{u}^{\mathrm{m}|} = \sum_{j=1}^{l} \Delta \mathbf{u}^{\mathrm{m}/+j}$$
$$= \sum_{j=1}^{t} \Delta j \mathbf{u}^{mj} + \sum_{j=1}^{l} R^{m,j}.$$

$h_i^{m,I} = \mathbf{v}_i^{mj+1} - \mathbf{v}_i^{\mathrm{m}j} = \sum_{j=1}^{l} \Delta_j \mathbf{v}_i^{m/+j} = \sum_{j=1}^{l} \Delta_j \mathbf{v}_i^{\mathrm{m}J} +$
$\sum_{j=1}^{l} r_i^{m,j}$. (12)

$\psi^{m,}, j = G^{\mathrm{mith}\ +Lj} - G^{mj,j}$,
$m \in \mathbb{N}, j = 1,2, \ldots J, l = 1,2, \ldots J, i = 1,2, \ldots, n.$
Moreover, we observe that by eq. (13)

$\|\psi^{m,t,j}\| = \|G^{mJ+l,j} - G^{mJ,j}\| \leq$
$\max_{1 \leq i \leq n} |g'(t_i)| \|\mathbf{x}^j\| \sum_{i=1}^{n} \|h_i^{m,l}\|$ (13)
$\leq \max_{1 \leq i \leq n} |g'(t_i)| \|\mathbf{x}^j\| \sum_{i=1}^{n} \sum_{k=1}^{l} \|\Delta_k \mathbf{v}_i^{mj+k}\|$
$\leq C_5 \eta_m,$

Combining $f_j'(t)$'s Lipschitz continuity, (14), we have by eq. (15)

$$\left|f_j'\left(\mathbf{u}^{mJ+j} \cdot G^{mJ+j,j}\right) - f_j'\left(\mathbf{u}^{mJ} \cdot G^{mJ+j,j}\right)\right|$$
$\leq L\left|\mathbf{u}^{mJ+j} \cdot G^{mJ+j,j} - \mathbf{u}^{mJ} \cdot G^{mJ+j,j}\right|$ (14)
$\leq L\|d^{m,j}\| \|G^{mj+j,j}\| \leq LC_3 \|d^{m,j}\|$
$\left|f_j'\left(\mathbf{u}^{mJ} \cdot G^{mj+j,j}\right) - f_j'\left(\mathbf{u}^{mj} \cdot G^{mj,j}\right)\right|$
$\leq L\left|\mathbf{u}^{mJ} \cdot G^{mJ+j,j} - \mathbf{u}^{mJ} \cdot G^{mJ,j}\right|$ (15)
$\leq L\|\mathbf{u}^{mJ}\| \|\psi^{m,j,j}\| \leq LC_2 \|\psi^{m,j,j}\|$

where L > 0 is Lipschitz constant. By definition of R m, j , we see that by eq. (16)

$$R^{m,j} = \Delta_j \mathbf{u}^{mj+j} - \Delta_j \mathbf{u}^{mj}$$
$$= -\eta_m \left(f_j'\left(\mathbf{u}^{mJ+j} \cdot G^{mJ+j,j}\right) G^{mJ+j.j} - f_j'\left(\mathbf{u}^{mJ} \cdot G^{mJ \cdot j}\right) G^{mJ.j}\right)$$
$$= -\eta_m \left[f_j'\left(\mathbf{u}^{mj+j} \cdot G^{mj+j,j}\right) \psi^{m,j,j}\right.$$
$$+ \left(f_j'\left(\mathbf{u}^{mJ+j} \cdot G^{mJ+j,j}\right) - f_j'\left(\mathbf{u}^{mJ} \cdot G^{mJ+j,j}\right)\right) G^{mJ,j}$$
(16)
$$\left. + \left(f_j'\left(\mathbf{u}^{mj} \cdot G^{mj+j,j}\right) - f_j'\left(\mathbf{u}^{mj} \cdot G^{mj,j}\right)\right) G^{mj,j}\right].$$

4. Experimental analysis:

The Google Colab environment and important Python libraries are used to implement the suggested method.

Data Description: A total of 952 people, including 372 women and 580 men, are chosen for this study who are 18 years of age or older. A questionnaire that was self-prepared based on factors that could cause diabetes was given to participants and is provided in Table 1. The same experiments were carried out on another database called PIMA Indian Diabetes database to confirm validity of model.

Table-1 Comparative analysis between proposed and existing technique based on various type-2 diabetes dataset

Parameters	**PIDD**	**SVM**	**BDPA_HD_MLA**
Accuracy	89	93	96
Precision	63	66	67
Recall	71	76	79
F1_Score	58	61	63
RMSE	63	63	66
MAP	65	67	68

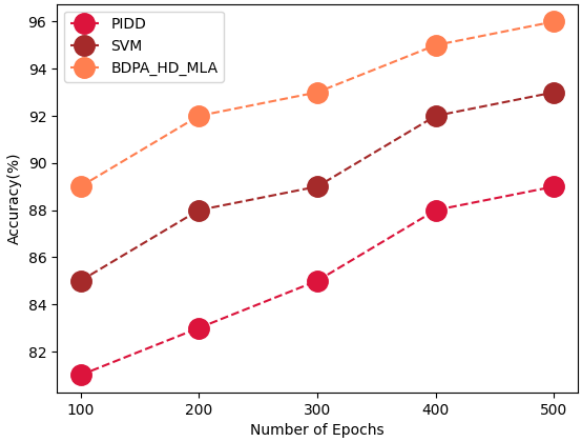

Figure-2 Comparison of accuracy

The above figure-2 shows comparative analysis between proposed and existing technique in terms of accuracy. The official definition of accuracy is as follows: The total number of accurate guesses is equal to the total number of accurate guesses. the comparison has been carried out based on number of users and here the proposed technique has attained accuracy of 96%, existing PIDD attained 89% and SVM attained 93%.

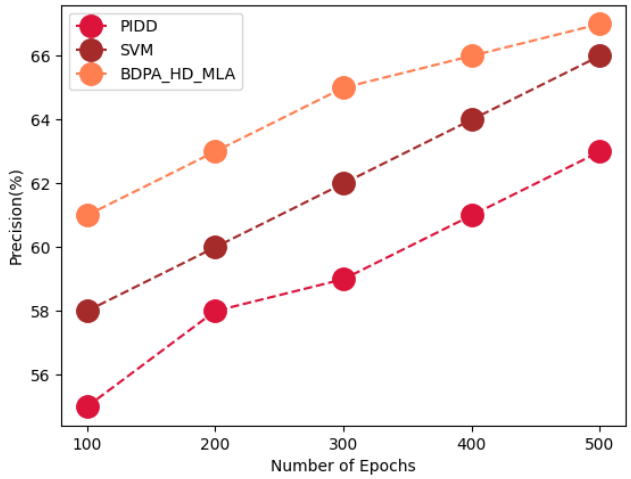

Figure-3 Comparison of precision

The comparison of precision between the proposed and existing techniques depending on the number of epochs is shown in figure 3 above. One indicator of system performance is precision, or quality of a successful prediction. Total number of accurate positive predictions is divided by total number of real positives to find precision. Proposed technique attained precision of 67%, existing PIDD attained 63% and SVM attained 66%.

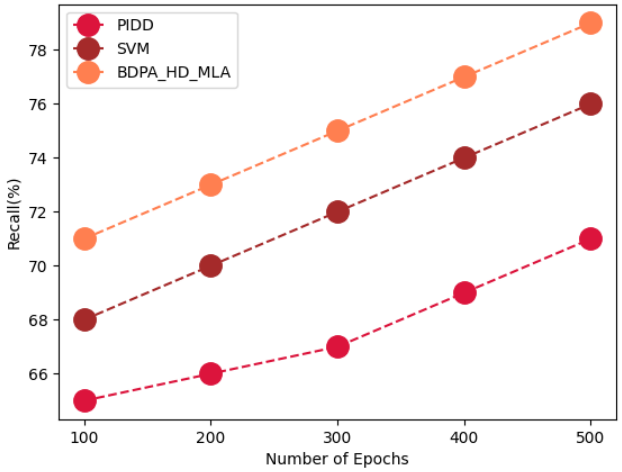

Figure-4 Comparison of recall

In figure 4 above, recall for the proposed and existing strategies is contrasted based on the quantity of users. Percentage of Positive samples that were accurately labelled as Positive relative to all Positive samples is how recall is evaluated. Proposed technique attained recall of 79%, existing PIDD attained 71% and SVM attained 76%.

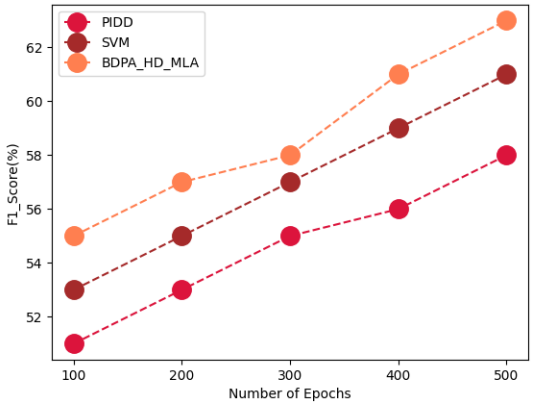

Figure-5 Comparison of F-1 score

Comparison of F-1 score between proposed and existing techniques is shown in figure 5 above. F1 Score is evaluated as weighted average of Precision and Recall. As a result, when determining this score, both FP and FN are taken into account. Particularly if you have an uneven class distribution. Proposed technique attained F-1 score of 63%, existing PIDD attained 59% and SVM attained 61%.

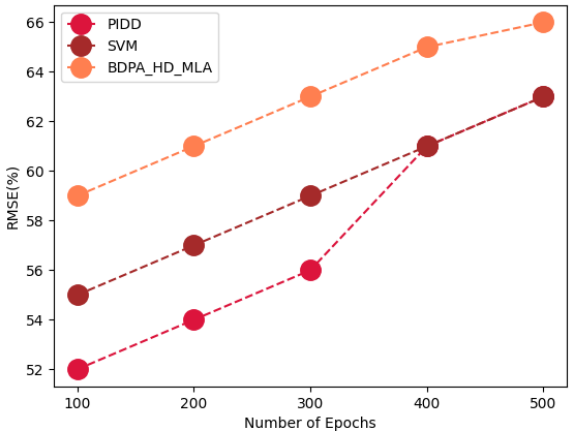

Figure-6 Comparison of RMSE

From above figure-6 the comparison of RMSE between proposed and existing technique. It illustrates the Euclidean distance between measured true values and forecasts. the proposed technique attained RMSE of 66%, existing PIDD attained 63% and SVM attained 63%.

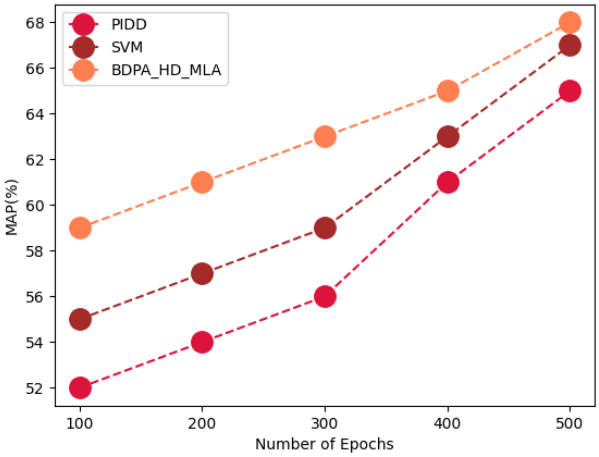

Figure-7 Comparison of MAP

From above figure-7 the comparison of MAP between proposed and existing technique. Using a model and a prior probability or belief about the model, MAP entails computing a conditional probability of observing the data. For machine learning, MAP offers an alternative probability framework to maximum likelihood estimation. Proposed technique attained MAP of 68%, existing PIDD attained 65% and SVM attained 67%.

5. Conclusion

This research propose novel technique in type 2 diabetes based heart disease detection in big data predictive analysis using machine learning technique. the processed data features has been extracted using regression model based linear discriminant analysis and classified using VGG-16 Net_gradient neural

network. Categorization and prediction accuracy of the current approach is not very good. In this study, we suggested a diabetes prediction model that combines a few extrinsic factors that cause diabetes in addition to more common parameters like glucose, body mass index (BMI), age, insulin, etc. Compared to the old dataset, the new dataset improves classification accuracy. The proposed method achieved 96% accuracy, 67% precision, 79% recall, a 63% F-1 score, a 66% RMSE, and a 68% MAP.

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