International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 7 July 2023, pp: 849-857 www.ijaem.net ISSN: 2395-5252

Enhanced Prediction of Diabetes Complications and Severity Analysis of Diabetic Retinopathy through Machine Learning, Image Processing and CNN

Dr MP Pushpalatha[1], Reena Mol VU[2],Sachit SS[3],M Roghini[3],Varun KG[3]

[1]*Professor, Dept.of CSE, JSS Science and Technology University, Mysuru,*
[2]*Research Scholar, Dept.of CSE,JSS Science and Technology University, Mysuru,*
[3]*Student, Dept.of CSE, JSS Science and Technology University, Mysuru.*

Date of Submission: 20-07-2023 Date of Acceptance: 31-07-2023

ABSTRACT: Diabetes mellitus is a potentially fatal chronic condition that can lead to severe complications in various body systems and requires early prevention. We aimed to create a system that can predict various diabetes complications and automate the diagnosis of diabetic retinopathy (DR) using machine learning methods and convolutional neural network. Firstly, this study employed supervised learning algorithms to build predictive models for classifying diabetes complications: metabolic syndrome, dyslipidemia, hypertension, obesity, and hyperglycemia. Several pre-processing techniques were used to handle imbalanced data in the dataset collected by National Health and Nutrition Examination Survey (NHANES). Then, top five and ten features were selected per complication, and performance estimation was done using repeated stratified k-fold cross-validation with 10 folds and 5 repetitions. The performance evaluation of the models was based on accuracy and F1-score, achieving a maximum of 98.8% for both metrics. Additionally, it was observed that using a subset of selected features still allowed for the development of effective classifiers. Secondly, this study presents a severity analysis of DR using convolutional neural networks (CNN) and fundus images. DR is a leading cause of blindness worldwide, and accurate diagnosis is crucial for timely treatment. The severity levels are mainly split into 7 classes namely based on Proliferative Diabetic Retinopathy and Non Proliferative Diabetic Retinopathy. The proposed approach shows promise for assisting ophthalmologists in the early detection and management of DR. Experimental results show that the CNN achieved an overall accuracy of 70% in accurately identifying DR severity levels. Validation data also had an accuracy of in and around 70%, therefore confirming that the model is well trained for unseen data as well. To summarize, this research utilized machine learning to forecast diabetes complications and analysed the severity of DR through image processing and convolutional neural networks, emphasizing the potential for precise diagnosis and effective treatment strategies.

KEYWORDS: Diabetes complications, Diabetic Retinopathy, CNN, supervised learning, fundus images

I. INTRODUCTION

One among the major modern life-style diseases is Diabetes. Day-by-day, the number of diseases increases because of the lifestyle changes in the modern era. Diabetes mellitus, or diabetes for short, is a chronic disease that occurs either when the pancreas does not produce enough insulin or when the body cannot effectively use the insulin it produces. Diabetes has two main types called type 1 and type 2. In type 1 diabetes (also known as insulin-dependent or childhood-onset), there is insulin production deficiency in the body, which requires daily administration of insulin, whereas in type 2 diabetes (known formally as non-insulin-dependent or adult-onset), the body cannot use insulin effectively.

There are different causes for diabetes. For instance, type 1 diabetes mellitus (T1DM) can develop due to an autoimmune reaction that

International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 7 July 2023, pp: 849-857 www.ijaem.net ISSN: 2395-5252

destroys the cells in the pancreas that make insulin, called beta cells , whereas type 2 diabetes is mainly caused by age, family history of diabetes, high blood pressure, high levels of triglycerides, heart disease or stroke . Early detection of diabetes can be of great benefit, especially because the progression of pre-diabetes to type 2 diabetes is quite high. According to CDC (Centres for disease Control and prevention), diabetes can affect any part of the body over time, leading to different types of complications. These complications are Hypertension, Obesity, Dyslipidemia, Metabolic syndrome, Diabetic foot, Neuropathy, Nephropathy and Retinopathy. To reduce the possibility of developing some serious complications related to diabetes, machine learning and data mining techniques can be applied to diabetes-related datasets. Several machine learning models were trained to classify the complications, namely, Logistic regression, Support Vector Machine (SVM), decision tree, Random forest, AdaBoost and XGBoost.

For the automated diagnosis of DR, Convolutional Neural Network model is used which also checks for the severity of the disease. Currently, detecting DR is a time-consuming and manual process that requires a trained clinician to examine and evaluate digital colour fundus photographs of the retina. By the time human readers submit their reviews, often a day or two later, the delayed results lead to lost follow up, miscommunication, and delayed treatment.

Clinicians can identify DR by the presence of lesions associated with the vascular abnormalities caused by the disease. While this approach is effective, its resource demands are high. The expertise and equipment required are often lacking in areas where the rate of diabetes in local populations is high and DR detection is most needed. As the number of individuals with diabetes continues to grow, the infrastructure needed to prevent blindness due to DR will become even more insufficient.

The need for a comprehensive and automated method of DR screening has long been recognized, and previous efforts have made good progress using image classification, pattern recognition, and machine learning. With colour fundus photography as input, the goal of this competition is to push an automated detection system to the limit of what is possible – ideally resulting in models with realistic clinical potential. The winning models will be open sourced to maximize the impact such a model can have on improving DR detection.

DR is a progressive eye disease associated with diabetes mellitus. By 2013 an estimated of 382 million people around the globe suffered DS, and by 2025 that number it is expected to increase up to 592 million.

The evaluation of DR is made by the examination of retinal fundus photographs that are taken with specialized fundus cameras. This evaluation is performed by ophthalmologists, who are trained to identify lesions in the eye. An early diagnosis of DR can prevent the progression of the DR, and therefore provide an effective treatment to the patient.

II. LITERATURE SURVEY

[1].This paper presents a robust framework for diabetes prediction where the outlier rejection, filling the missing values, data standardization, feature selection, K-fold cross-validation, and different Machine Learning (ML) classifiers (k-nearest Neighbour, Decision Trees, Random Forest, AdaBoost, Naive Bayes, and XGBoost) and Multilayer Perceptron (MLP) were employed. The framework proposed in the paper outperforms other frameworks which are used to predict diabetes using Pima Indian Diabetes Dataset.

[2].The authors evaluated the effectiveness of machine algorithms in predicting risks of complications and poor glycemic control in nonadherent type 2 diabetes. 18 prediction models were developed using seven types of machine learning algorithms. According to authors, the duration of T2D and the duration of unadjusted hypoglycemic treatment were the key risk factors of diabetic complications. After performance analysis they selected different machine learning models for various complications.

[3].The most common diabetes microvascular complications among Indonesian population are retinopathy, nephropathy and neuropathy. In order to prevent these complications to manifest, data mining technique to extract knowledge of risk factor for each complication becomes crucial. The authors constructed a prediction model for three major diabetic complications and found out the significant features associated with it. They used various machine learning models such as Naïve Bayes Tree, C4.5 decision tree-based classification techniques and K-means clustering techniques to analysis the dataset. After this analysis, they evaluated the performance of each technique and found the correlated feature and sub feature as a disease risk factor for them. The overall accuracy of the proposed model is 68%.

[4].In this model, the authors dealt with the missing value by means of random forest and used suitable

International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 7 July 2023, pp: 849-857 www.ijaem.net ISSN: 2395-5252

strategies to handle class balance. They predicted the onset of retinopathy, neuropathy and nephropathy with the help of Logistic Regression model with stepwise feature selection. The variables considered are gender, age, time from diagnosis, BMI, glycated haemoglobin, hypertension and smoking habit. The accuracy obtained was 83.8.

[5].The proposed model uses time series data of a year that contains 164 features including results of different pathological tests. Methods such as Logistic Regression, SVM, Naïve Bayes, Decision Tree and Random Forest have been used in a supervised environment to predict the probability of Diabetes induced Nephropathy and Cardiovascular diseases. Various training models were used to compare their performance in predicting the risk of Diabetes induced Nephropathy and Cardiovascular diseases. In this paper authors concentrated on only two diabetic complications.

[6].Authors developed a model in which they used multiresolution based decomposition of Discrete Wavelet Transform (DWT) for feature selection and CNN for classification for grading DR images. The proposed process begins by pre-processing technique by using Contrast Limited Adaptive Histogram Equalization (CLAHE). The proposed model achieved an accuracy of 90.07%, 96.20% and 93.53% for all DR stages.

[7].Proposed method developed for severity grading and lesion detection from retinal fundus images are used as computer-aided diagnosis system to support the clinical diagnosis. The authors used transfer learning with CNN called EfficientNet-B3 and the publically available Kaggle Asia Pacific Tele-Ophthalmology Society (APTOS) 2019 training dataset. The proposed method achieved classification accuracy values of 0.84, 0.95 and 0.98 for 1st, 2nd and 3rd predicted labels.

[8].The major contribution of authors in this paper, isaboutusingconvolutionalneural network algorithms with deeplearning as core component formedical image detection andsegmentation with high-performance and low-latencyinference. This paper also establishes asystemincreasetheefficiencyand accuracy of NPDR (non-proliferated diabeticretinopathy)prediction. The one of the limitations of this proposedresearch is that, it exceedsexistingtechnology andtherefore makes the implementation difficult.

[9].This paper discusses about thedesign of a software-basedalgorithm for early diagnosis of DiabeticRetinopathy.Thepaperuses MATLAB based imageprocessing to identify whitishlesions, cotton wool spots andhard exudates associated withDR. Based on the value of pixelcounts patient is classified as aDiabeticor Non-DiabeticRetinopathic. In this model, authors did not consider features ofdiabeticretinopathy suchas hemorrhages,reddish lesions,and micro aneurysms.

[10].For improved DR severity classification the authors proposed a hybrid machine learning system which combine CNNs with dictionary based approaches for DR severity prediction from retinal fundus images. The system consists of CNN trained for DR prediction, a pre-trained ImageNet CNN, a Support Vector Machine and Random Forest classifiers. This new method achieved higher classification accuracy of 0.86 compared to baseline CNN method.

III. PROPOSED SYSTEM

For prediction of diabetic complications-

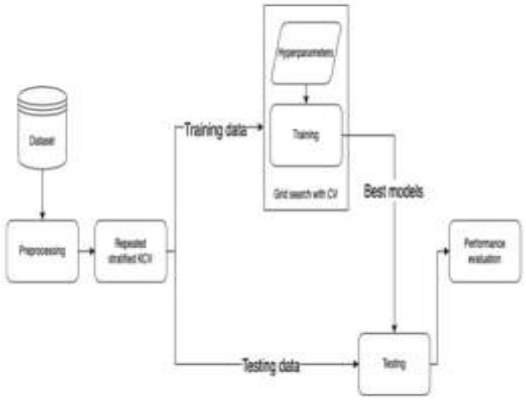

Fig.1 depicts the workflow of the process

Dataset

The dataset collected by National Health and Nutrition Examination Survey (NHANES) was utilised here. The dataset consists of 1931 patients with 17 input attributes and five complications (target). The input attributes include age, BMI, trigylcerides, albuminuria,uricAcid, bloodglucose, etc. and the target include metabolic syndrome, dyslipidemia, hyperglycemia, hypertension and obesity.

\Data Pre-processing

Data cleaning: In the dataset, attributes such as name and annual income leading to confidentiality were removed.

Categorical encoding: Encoding is necessary when ML algorithms require numerical data and therefore cannot handle categorical values. For this purpose, one-hot encoding was applied on

International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 7 July 2023, pp: 849-857 www.ijaem.net ISSN: 2395-5252

features such as gender, race, smoking habit and marital status.

Data balancing: Addressing the challenge of an unbalanced dataset, undersampling using cluster centroids was applied. This technique clusters majority class samples and selects representative instances from the centroids to create a balanced subset, effectively reducing the class imbalance.

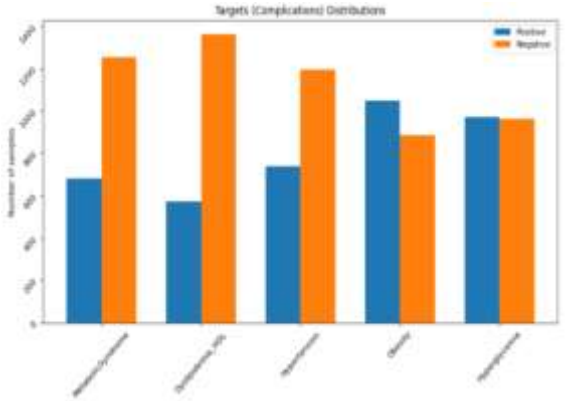

Fig.2 distributions of classes in each complication before data balancing

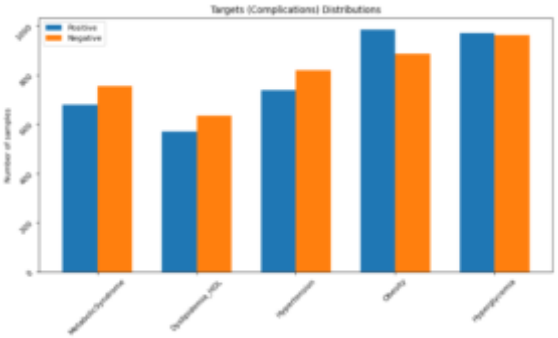

Fig.3 distributions of classes in each complication after data balancing

Data normalisation: Given that the dataset primarily consists of numerical attributes, it is crucial to address variations in measurement units. To mitigate any impact on model performance, normalization was employed to rescale all numeric features to a range of 0 to 1.The below normalization formula was used, where Value is the value needed to be normalized, Max and Min are the maximum and minimum values respectively in the column.

$$\frac{\text{Value} - \text{Min}}{\text{Max}}$$

Machine learning models

Different supervised algorithms such as Logistic Regression, SVM, AdaBoost, XGBoost, Decision Tree and Random Forest were used to train the models.

Model training

After processing the dataset and selecting the machine learning algorithms to be used, the next step was to build the actual models by training each algorithm using the processed dataset.

Cross-validation: K-fold cross-validation is a widely used technique to assess machine learning model performance. The dataset was divided into k folds, with k-1 folds used for hyperparameter tuning using grid search in the inner loop. In the outer loop, the best hyperparameters and test data were utilized to evaluate the model. Stratified KCV was employed to account for imbalanced records, maintaining class proportions. To enhance evaluation, this process was repeated 10 times.

Feature selection: Following model training with the optimized hyperparameters, feature selection techniques were implemented using Recursive Feature Elimination. The top five and ten attributes were selected for each model. A performance comparison was performed to analyze the impact of using all features versus the selected ones for constructing various ML classifiers.

Evaluation metrics: Accuracy score and F1-score were used to evaluate the performance of the trained models for each complication. The accuracy of a classifier can be computed using the below equation where TP is true positive, TN is true negative, FP is false positive, FN is false negative.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} * 100\%$$

F1-score calculated using the below equation.

$$\text{F1} - \text{score} = \frac{2 * \text{Precison} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

where $\text{Recall} = \frac{\text{TP}}{\text{TP}+\text{FN}}$ and $\text{Precision} = \frac{\text{TP}}{\text{TP}+\text{FP}}$.

For Severity Analysis of Diabetic Retinopathy-

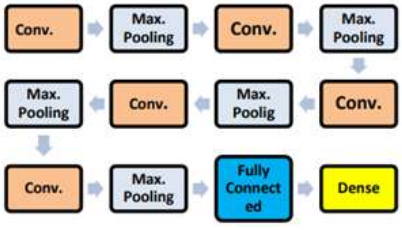

Fig.5 depicts the workflow of the process

International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 7 July 2023, pp: 849-857 www.ijaem.net ISSN: 2395-5252

Data Collection and Dataset Preparation

Messidor dataset consists of 1,200 colour fundus images acquired from diabetic patients. MESSIDOR stands for Methods to evaluate Segmentation and Indexing Techniques in the field of Retinal Ophthalmology. The images cover different stages of DR severity namely No DR, NPDR, Moderate NPDR, Severe NPDR, PDR, Severe PDR.

Data Pre-processing

Forpre-processingthedata,specificstepsarefollowedsuchas,Read all the input .jpeg or .jpg images saved in the directory , Translate the image filesinto pixels arranged as RGB grids with channels , For input, Decode them into floating-pointtensors ,Rescalepixel valuestothe[0,1]interval. Perform one hot encoding to change the categorical values appropriately and also perform data augmentation to train the model more effectively.

```
# Data augmentation
data_augmentation = tf.keras.Sequential([
    layers.experimental.preprocessing.RandomRotation(0.2),
    layers.experimental.preprocessing.RandomZoom(0.2),
    layers.experimental.preprocessing.RandomFlip("horizontal"),
    layers.experimental.preprocessing.RandomContrast(0.2),
])
```

Fig.6 Data Augmentation

Trainingthemodel

The 7 LayeredCNNisTrainedusingthefeaturesextractedfromtheinputmessages.Thelayers areas follows:

- **layers.experimental.preprocessing.Rescaling(1./255, input_shape=(256, 256, 3))**

This layer performs rescaling of the input images. It divides the pixel values by 255 to normalize them between 0 and 1. It also specifies the input shape of the images as (256, 256, 3), which represents a height of 256, width of 256, and 3 color channels (RGB).

- **layers.Conv2D(16, 3, padding='same', activation='relu')**

This is a convolutional layer with 16 filters, each of size 3x3. It applies a set of 2D filters to the input image to extract local features. The 'same' padding ensures that the output has the same spatial dimensions as the input. The ReLU activation function introduces non-linearity to the output.

- **layers.MaxPooling2D()**

This layer performs max pooling, which reduces the spatial dimensions of the input by taking the maximum value within each pooling window. It helps in down sampling and extracting the most important features.

- The next three layers (layers.Conv2D, layers.MaxPooling2D) follow a similar pattern, increasing the number of filters (32 and 64) to extract more complex features and further downsample the input.
-
- **layers.Flatten()**

This layer flattens the multi-dimensional output from the previous layer into a 1D vector. It prepares the data for passing through fully connected layers.

- **layers.Dense(128, activation='relu')**

This is a fully connected layer with 128 units. Each unit is connected to every unit in the previous layer. The ReLU activation function introduces non-linearity to the output.

- **layers.Dense(7, activation='softmax')**

This is the final fully connected layer with 7 units. It uses the softmax activation function, which normalizes the outputs into a probability distribution over the 7 classes. Each unit represents the probability of the input belonging to a particular class.

International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 7 July 2023, pp: 849-857 www.ijaem.net ISSN: 2395-5252

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 254, 254, 32)      896

max_pooling2d (MaxPooling2D  (None, 127, 127, 32)      0
)

conv2d_1 (Conv2D)            (None, 125, 125, 64)      18496

max_pooling2d_1 (MaxPooling  (None, 62, 62, 64)        0
2D)

conv2d_2 (Conv2D)            (None, 60, 60, 128)       73856

max_pooling2d_2 (MaxPooling  (None, 30, 30, 128)       0
2D)

conv2d_3 (Conv2D)            (None, 28, 28, 256)       295168

max_pooling2d_3 (MaxPooling  (None, 14, 14, 256)       0
2D)

flatten (Flatten)            (None, 50176)             0

dense (Dense)                (None, 512)               25690624

dense_1 (Dense)              (None, 256)               131328

dense_2 (Dense)              (None, 7)                 1799

=================================================================
Total params: 26,212,167
Trainable params: 26,212,167
Non-trainable params: 0
```

Fig.7Neural Network Architecture

Testing

Various new images are tested and the trained CNN model is evaluated for it's a ccuracyrate.

IV. RESULTS

In order to optimize hyperparameters and train the models effectively, we employed k-fold cross-validation (k=5) for hyperparameter tuning and repeated k-fold cross-validation (k=10) with 5 repetitions formodel training. This resulted in a total of 250 experiments for each model.

Complication	Algorithms	All attributes		Top 10		Top 5	
		Accuracy score	F1-Score	Accuracy score	F1-Score	Accuracy score	F1-Score
Metabolic Syndrome	LR	0.764	0.764	0.771	0.771	0.752	0.751
	SVM Linear	0.769	0.769	0.785	0.784	0.763	0.763
	Adaboost	0.850	0.850	0.840	0.839	0.795	0.794
	XGBoost	**0.881**	**0.881**	**0.877**	**0.876**	**0.810**	**0.811**
	Random Forest	0.871	0.870	0.860	0.859	0.815	0.714
	Decision Tree	0.649	0.646	0.649	0.646	0.637	0.634
Dyslipidemia_HDL	LR	0.873	0.873	0.895	0.895	0.916	0.916
	SVM Linear	0.935	0.935	0.940	0.939	0.942	0.942
	Adaboost	**0.988**	**0.988**	**0.987**	**0.987**	**0.977**	**0.977**
	XGBoost	0.898	0.898	0.877	0.877	0.888	0.888
	Random Forest	0.897	0.897	0.877	0.877	0.866	0.867
	Decision Tree	0.738	0.735	0.703	0.700	0.707	0.704
Hypertension	LR	0.648	0.647	0.654	0.653	0.652	0.652
	SVM Linear	0.648	0.647	0.648	0.648	0.650	0.649
	Adaboost	0.650	0.650	0.647	0.646	0.624	0.619
	XGBoost	0.685	0.683	0.673	0.677	0.655	0.654
	Random Forest	**0.736**	**0.734**	**0.744**	**0.743**	**0.720**	**0.722**
	Decision Tree	0.678	0.675	0.676	0.673	0.687	0.685
Obesity	LR	0.941	0.941	0.944	0.944	0.948	0.948
	SVM Linear	0.964	0.964	0.966	0.966	0.967	0.967
	Adaboost	**0.987**	**0.986**	**0.978**	**0.978**	**0.977**	**0.977**
	XGBoost	0.977	0.977	0.955	0.955	0.949	0.949
	Random Forest	0.871	0.870	0.860	0.859	0.815	0.714
	Decision Tree	0.800	0.799	0.803	0.802	0.780	0.779
Hyperglycemia	LR	0.776	0.775	0.773	0.773	0.782	0.782
	SVM Linear	0.854	0.854	0.860	0.859	0.864	0.863
	Adaboost	**0.889**	**0.889**	**0.898**	**0.898**	**0.867**	**0.867**
	XGBoost	0.881	0.881	0.877	0.876	0.810	0.811
	Random Forest	0.850	0.850	0.840	0.839	0.795	0.794
	Decision Tree	0.738	0.735	0.703	0.700	0.707	0.704

Fig.8accuracy score and F-1 score obtained for all experiments

International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 7 July 2023, pp: 849-857 www.ijaem.net ISSN: 2395-5252

The accuracy during training and validation accuracy of the trained CNN model is plotted for better visualisation. After employing data augmentation the model was better trained to predict the severity of DR.

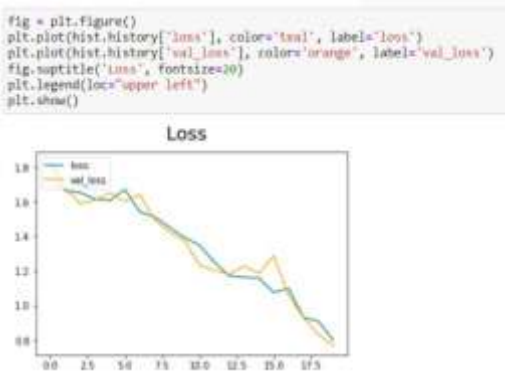

Fig.9 Training and Validation Loss

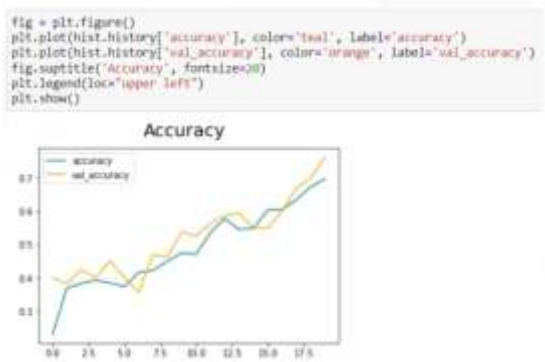

Fig.10 Training and Validation Accuracy

V. DISCUSSION

The impressive performance of Random Forest, AdaBoost and XGBoost underscores the significance of employing tree-based ensemble algorithms in these problem domains. Moreover, certain cases showed strong performance from linear models, particularly logistic regression, reaffirming the validity of linearity assumptions. Furthermore, consistent results indicated that the same algorithm consistently yielded the best outcomes, regardless of attribute selection. Features such as total age, gender, BMI, and HDL (high-density lipoprotein) showed satisfactory results, suggesting the importance of these features in developing more sophisticated models. Training times varied marginally across algorithms, with ensemble methods generally requiring the most time. However, given the dataset's small size, time differences were disregarded when selecting the best models.

For Severity Analysis of DR, an impressive accuracy of 70% was obtained for the given trained model. The given CNN was trained on a dataset of in and around 1000 images. Therefore catering to the complexity and size of the given dataset, the architecture of the CNN is tweaked and changed accordingly to provide best accuracy. Extra care was given to make sure that overfitting doesn't take place and the trained model performs well for unseen data as well. The model was trained over 20 epochs. However there are a few shortcomings, firstly the dataset is not as balanced as is required and its size can be increased. If data size is increased testing data can also be increased, therefore the CNN model can be tested for unseen data and the architecture of the CNN model can be changed accordingly based on the testing accuracy.

VI. CONCLUSION

An extensive search was conducted for precise and diverse datasets to enhance the accuracy of predicting diabetes complications. These datasets were chosen with care to include a variety of features, addressing the problems of overfitting and underfitting frequently seen in prediction models. We trained the data using different algorithms, such as XGBoost, Adaboost, Logistic Regression, SVM, Decision Tree and Random Boost Classifier, to identify the best-performing model for each complication. Our goal is to find the model with the highest accuracy that can successfully predict each complication.We have also looked into how well image segmentation methods can foretell DR stages. The identification of particular regions of interest in medical images is facilitated by image segmentation. We concentrated on segmenting blood vessels and hard exudates, which are significant indicators of DR in colour eye fundus images. We have created effective method for extracting these features from fundus images while taking image content, texture, and intensity into account. The outcomes of our simulation on a fundus dataset show that the suggested methodology can accurately identify hard exudates, reducing human errors and possibly offering services in remote locations where access to specialised healthcare may be limited.

REFERENCES

[1]. Hasan, M.K., Alam, M.A., Das, D., Hossain, E. and Hasan, M., 2020. Diabetes prediction using ensembling of different machine learning classifiers. IEEE Access, 8, pp.76516-76531.

[2]. Fan, Y., Long, E., Cai, L., Cao, Q., Wu, X. and Tong, R., 2021. Machine learning approaches to predict risks of diabetic

complications and poor glycemic control in nonadherent type 2 diabetes. Frontiers in Pharmacology, 12, p.665951.

[3]. Fiarni, C., Sipayung, E.M. and Maemunah, S., 2019. Analysis and prediction of diabetes complication disease using datamining algorithm. Procedia computer science, 161, pp.449-457.

[4]. Dagliati, A., Marini, S., Sacchi, L., Cogni, G., Teliti, M., Tibollo, V., De Cata, P., Chiovato, L. and Bellazzi, R., 2018. Machine learning methods to predict diabetes complications. Journal of diabetes science and technology, 12(2), pp.295-302.

[5]. Sosale, A., Kumar, K.P., Sadikot, S.M., Nigam, A., Bajaj, S., Zargar, A.H. and Singh, S.K., 2014. Chronic complications in newly diagnosed patients with type 2 diabetes mellitus in India. Indian journal of endocrinology and metabolism, 18(3), p.355.

[6]. Ashwini, K. and Dash, R., 2023. Grading diabetic retinopathy using multiresolution based CNN. Biomedical Signal Processing and Control, 86, p.105210.

[7]. Sugeno, A., Ishikawa, Y., Ohshima, T. and Muramatsu, R., 2021. Simple methods for the lesion detection and severity grading of diabetic retinopathy by image processing and transfer learning. Computers in Biology and Medicine, 137, p.104795.

[8]. Qiao, L., Zhu, Y. and Zhou, H., 2020. Diabetic retinopathy detection using prognosis of microaneurysm and early diagnosis system for non-proliferative diabetic retinopathy based on deeplearning algorithms. IEEE Access, 8, pp.104292-104302.

[9]. Gautam, A.S., Jana, S.K. and Dutta, M.P., 2019, May. Automated Diagnosis of Diabetic Retinopathy using image processing for non-invasive biomedical application. In 2019 International Conference on Intelligent Computing and Control Systems (ICCS) (pp. 809-812). IEEE.Roy, P., Tennakoon, R., Cao, K., Sedai, S., Mahapatra, D., Maetschke, S. and Garnavi, R., 2017, April.A novel hybrid approach for severity assessment of diabetic retinopathy in colour fundus images.In 2017 IEEE 14th International Symposium on Biomedical Imaging (ISBI 2017) (pp. 1078-1082). IEEE.

[10]. Roy, P., Tennakoon, R., Cao, K., Sedai, S., Mahapatra, D., Maetschke, S. and Garnavi, R., 2017, April. A novel hybrid approach for severity assessment of diabetic retinopathy in colour fundus images. In 2017 IEEE 14th International Symposium on Biomedical Imaging (ISBI 2017) (pp. 1078-1082). IEEE.

[11]. Qomariah, D.U.N., Tjandrasa, H. and Fatichah, C., 2019, July. Classification of diabetic retinopathy and normal retinal images using CNN and SVM. In 2019 12th International Conference on Information & Communication Technology and System (ICTS) (pp. 152-157). IEEE.

[12]. Sambyal, N., Saini, P. and Syal, R., 2020. Microvascular complications in type-2 diabetes: a review of statistical techniques and machine learning models. Wireless Personal Communications, 115, pp.1-26.

[13]. Jung, Y. and Kim, D., 2022. Feature Extraction of Non-proliferative Diabetic Retinopathy Using Faster R-CNN and Automatic Severity Classification System Using Random Forest Method. Journal of Information Processing Systems, 18(5).

[14]. Putra, R.E., Tjandrasa, H. and Suciati, N., 2020. Severity Classification of Non-Proliferative Diabetic Retinopathy Using Convolutional Support Vector Machine. International Journal of Intelligent Engineering & Systems, 13(4).

[15]. Prabhavathy, P., Tripathy, B.K. and Venkatesan, M., 2022. Analysis of diabetic retinopathy detection techniques using CNN models. In Augmented Intelligence in Healthcare: A Pragmatic and Integrated Analysis (pp. 87-102). Singapore: Springer Nature Singapore.

[16]. Maswood, M.M.S., Hussain, T., Khan, M.B., Islam, M.T. and Alharbi, A.G., 2020, November. Cnn based detection of the severity of diabetic retinopathy from the fundus photography using efficientnet-b5. In 2020 11th IEEE Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON) (pp. 0147-0150). IEEE.

[17]. Asia, A.O., Zhu, C.Z., Althubiti, S.A., Al-Alimi, D., Xiao, Y.L., Ouyang, P.B. and Al-Qaness, M.A., 2022. Detection of diabetic retinopathy in retinal fundus images using CNN classification models. Electronics, 11(17), p.2740.

[18]. Papatheodorou, K., Papanas, N. and Banach, M., 2016. papazoglou, D., & Edmonds, M.(2016). Complications of Diabetes, 2016.

[19]. Unnikrishnan, R., Anjana, R.M. and Mohan, V., 2016. Diabetes mellitus and its complications in India. Nature Reviews Endocrinology, 12(6), pp.357-370.

[20]. Tönnies, T., Stahl-Pehe, A., Baechle, C., Castillo, K., Kuss, O., Yossa, R., Lindner, L.M., Holl, R.W. and Rosenbauer, J., 2018. Risk of microvascular complications and macrovascular risk factors in early-onset type 1 diabetes after at least 10 years duration: an analysis of three population-based cross-sectional surveys in Germany between 2009 and 2016. International Journal of Endocrinology, 2018.

[21]. Afroz, A., Zhang, W., Loh, A.J.W., Lee, D.X.J. and Billah, B., 2019. Macro-and micro-vascular complications and their determinants among people with type 2 diabetes in Bangladesh. Diabetes & Metabolic Syndrome: Clinical Research & Reviews, 13(5), pp.2939-2946.

[22]. Bansal, D., Gudala, K., Esam, H.P., Nayakallu, R., Vyamusani, R.V. and Bhansali, A., 2014. Microvascular complications and their associated risk factors in newly diagnosed type 2 diabetes mellitus patients. International journal of chronic diseases, 2014.

[23]. Cheema, S., Maisonneuve, P., Zirie, M., Jayyousi, A., Alrouh, H., Abraham, A., Al-Samraye, S., Mahfoud, Z., Al-Janahi, I.M., Ibrahim, B. and Lowenfels, A.B., 2018. Risk factors for microvascular complications of diabetes in a high-risk middle east population. Journal of diabetes research, 2018.

[24]. Abougalambou, S.S.I. and Abougalambou, A.S., 2015. Risk factors associated with diabetic retinopathy among type 2 diabetes patients at teaching hospital in Malaysia. Diabetes & Metabolic Syndrome: Clinical Research & Reviews, 9(2), pp.98-103.

[25]. Jian, Y., Pasquier, M., Sagahyroon, A. and Aloul, F., 2021, December. A machine learning approach to predicting diabetes complications.In Healthcare (Vol. 9, No. 12, p. 1712).MDPI.