

DeepRetina: Detection of Diabetic Retinopathy

MR. DEEPAK SHIVAPPA YENECHAWANDI

Ashokrao Mane Group Of Institution, Vathar
Department of Computer Science and Engineering
deepakyenechawandi@gmail.com

MR. SHRIDHAR GAJANAN KUMBHAR

Ashokrao Mane Group Of Institution, Vathar
Department of Computer Science and Engineering
shridhargk2004@gmail.com

MR. VISHNU DATTATRAY SHINDE

Ashokrao Mane Group Of Institution, Vathar
Department of Computer Science and Engineering
vs0663529@gmail.com

MR. PRUTHIVIRAJ MARUTI KADAM

Ashokrao Mane Group Of Institution, Vathar
Department of Computer Science and Engineering
pruthvi1269@gmail.com

MR. ADITYA ANIL KHOCHIKAR

Ashokrao Mane Group Of Institution, Vathar
Department of Computer Science and Engineering
adityakhochikar@gmail.com

MISS. MRUNAL MADHAV PAWAR

Ashokrao Mane Group Of Institution, Vathar
Department of Computer Science and Engineering
mmp@amgoi.edu.in

Abstract : Diabetic Retinopathy is one of the common complications in diabetes and one of the most common cause of visual loss if undiagnosed and unmanaged. The rise in the diabetic case's population has led to a demand of effective and automated webbing systems. The present paper focus on the deep literacy based system for opinion of diabetic retinopathy by discovery and bracket of retinal fundus images.

This system name is DeepRetina.

The presented system uses Convolutional Neural Networks(CNN) and transfer literacy to automatically learn the features from the retinal images and classify them into colorful situations of diabetic retinopathy inflexibility. While the conventional machine literacy ways are more focused on point birth and use different classifiers like Support Vector Machine(SVM), it requires homemade point birth and further computationally precious compared to deep literacy. The deep literacy models with transfer literacy has overcome this issue by enabling it to learn more complex features automatically from retinal fundus images.

Before feeding the images to the trained model, image processing ways like normalization, discrepancy improvement and data balancing are used for better result and delicacy of bracket. The model is trained and tested using readily available public datasets APTOS and EyePACS that are extensively used for diabetic retinopathy discovery and bracket. It shows that deep literacy grounded system achieves better delicacy and robustness for this task.

The advanced system also aims to achieve real- time vaticination and can be extended to the scalable perpetration of web interface for availability. The advanced system help medical interpreters for effective identification of diabetic retinopathy at the early stage, reduces the burden of the differentia and increase availability to eye care installations.

INDEX TERMS: Artificial Intelligence, Convolutional Neural Network, Deep Learning, Diabetic Retinopathy, Resolvable AI, Image Processing, Medical Image Analysis, Transfer Learning

1.INTRODUCTION

Diabetic Retinopathy(DR) is a complication of long- term diabetes, which affects the blood vessels in the retina and may

lead to loss of vision. It's the most common cause of vision loss

in the working- age population, encyclopedically. frequently, in the early stages, it may be asymptomatic, hence beforehand discovery is of consummate significance to help endless damage to the eyes. Reports suggest that a significant number of diabetic individualities will ultimately develop retinopathy.

Homemade examination of the retinal fundus images by ophthalmologists has been the current system for the opinion of DR. Manual examination, still, requires an expert's time and cost and has a constraint on vacuity of ophthalmologists, particularly in pastoral and less advanced areas. likewise, homemade examination has been subject to variability and detention in the opinion process. Machine literacy- grounded ways similar as SVMs and point- grounded approaches have been experimented for automatic and early discovery, but their performance relies on hand- drafted features and good image quality.

More lately, state- of- the- art results for the automatic medical image analysis have been reported due to tremendous progresses in Deep Learning. CNNs have demonstrated to be veritably effective to automatically prize features directly from retinal fundus images barring homemade point engineering tasks. Indeed, experimenters employed CNN- grounded infrastructures, similar as AlexNet, Inception, ResNet in discovery and bracket of DR and generally made use of transfer literacy to enhance performance where a model trained on a massive image database(non medical) is used in the medical imaging sphere to manage with the size limitation of the data.

While great success has been achieved, issues like data imbalance, lack of interpretability and the need for practical perpetration in clinical workflow still persist. In this work, we introduce DeepRetina which is an automated deep literacy system for DR discovery and bracket using preprocessing, transfer literacy and resolvable AI ways to gain results that are accurate as well as interpretable and is developed as a web- grounded operation to enable real- time diagnostics, making it suitable for large- scale webbing and clinical practice.

2. LITERATURE REVIEW:

Originally, research in the detection of diabetic retinopathy was predominantly using classical machine learning together with image processing. Hand-crafted features, such as blood vessels patterns, microaneurysm and exudates, were extracted from retinal images. These features were then fed into a classifier like Support Vector Machines and Principal Component Analysis, for the detection of diseases. Although such techniques have reported high performance on clean datasets in a controlled environment, its accuracy was heavily dependent on the quality of feature extraction and

preprocessing stages, and therefore did not adapt well in practice .

Inspired by the significant performance improvements in a wide range of applications, deep learning architectures, particularly CNN, has been adopted to enable the automatic DR detection without explicit feature engineering. Hierarchical features have been learned directly from raw retinal images using architectures like AlexNet and other custom CNN models on large datasets like APTOS and EyePACS. These models have yielded remarkable results in classification, reporting accuracies above 90%, confirming the efficacy of deep learning models in medical image analysis .

To optimize classification performance, transfer learning, as well as ensembling techniques were utilized to further boost the accuracy and generality. Existing pre-trained deep learning models like ResNet, ShuffleNet and Inception were fine-tuned for the DR detection task in an attempt to learn high-quality features despite limited training data. Some methods have combined several models with an optimization framework in terms of feature weighting and parameter tuning to improve performance further. These improved methods had achieved a good performance for both binary classification and multi-class classification tasks .

Besides the image based approaches, some research explored the prediction of diabetic retinopathy based on patients related clinical information like age, body mass index and patient medical history, using machine learning approaches like logistic regression, k-nearest neighbor and SVM. Although such approach yielded good result and it could be beneficial to identify at-risk patients, the accuracy was still relatively poor comparing to image-based deep learning models. To achieve a more robust prediction performance, there have been researches on ensembling multiple models to develop a strong predictor. Despite the development, it still remains that a general lack of interpretability, a problem of dataset imbalance and the challenges in real-world deployment still persisted.

3. PROPOSED SYSTEM:

3.1. System description:

DeepRetina is an intelligent automated platform designed for early detection and classification of Diabetic Retinopathy using retinal fundus images. Our solution is intended to tackle the challenges of human diagnosis,

ensuring speed, consistency, and scalability while aiding healthcare professionals in decision making. By employing advanced deep learning methods to analyze retina images, our system is able to discern subtle signs of the disease often unnoticeable by manual inspection, leading to early diagnosis and prevention of significant visual impairment.

The system works by processing images through a well-defined pipeline, beginning with the acquisition and meticulous preprocessing of retinal fundus images, followed by automated feature extraction and classification via a trained deep learning model. For optimized performance and accelerated training, we leverage a pre-trained Convolutional Neural Network through transfer learning. The preprocessing step ensures uniformity across all input images by applying normalization, resizing and contrast enhancement techniques to optimize input quality for accurate classification. The classification model categorizes retinal fundus images according to the various stages of diabetic retinopathy, generating precise diagnostic conclusions.

To improve user experience and enhance clinical application, the developed system is presented as an easy-to-use web-based application. Users can readily upload images and get immediate diagnostic predictions along with critical highlight regions in retinal fundus images through integrated explainable AI approaches, aiding in better understanding of predictions and model outcomes. The solution is scalable, efficient and accessible for implementation in clinics, hospitals and remote settings where specialized skills are not readily available.

3.2. Functional Modules:

1. Image Input Module

This is the initial component that allows users to upload their retinal fundus images via the web-based application. It supports common image file formats such as JPEG and PNG and also provides basic validation to confirm the input image satisfies the basic criteria of quality and format required for processing. The module is simple to use for all kinds of users, from medical practitioners to the non-expert, to interact with the application.

2. Image Preprocessing Module

The aim of this module is to improve the quality of the input image so that analysis is carried out reliably. The retinal images can vary in terms of imaging device, lighting conditions and resolution; this module standardizes the images. It includes steps such as resizing to match the input requirements of the model, normalization of pixel intensities, noise reduction, and contrast enhancement to improve clarity of retinal features (blood vessels and lesions) in order to enhance the performance of the deep learning model.

3. Feature Extraction and Classification Module

This is the core component where the system applies deep learning for disease detection. The module uses a pre-trained CNN (such as Inception V3) along with transfer learning to extract informative features from retinal fundus images. A deep learning model will automatically determine complex features and classify them into various grades of DR (no DR, mild, moderate, severe and proliferative) with a high degree of accuracy and removes the laborious manual feature engineering process.

4. Explainable AI Module

This module increases the transparency and trust of the DeepRetina system. The explainable AI module is able to produce heat maps that are based on techniques such as Grad-CAM in order to highlight specific areas in the retinal image that affected the prediction result. These heat maps provide medical practitioners with an understanding that the model has focused on appropriate clinically significant features in the retina for accurate diagnosis and predictions, thereby building trust in the automated diagnosis result.

5. Multi-Disease Screening Module

This module screens other retinal diseases such as glaucoma, cataract, and age-related macular degeneration alongside the detection of DR. The module allows for more comprehensive diagnosis and also aids in screening multiple diseases at once with either the use of additional pre-trained models or rule based systems for multi-disease detection.

6. Report Generation Module

This module generates comprehensive and detailed reports of the diagnosis that include the predicted severity, confidence level, heat maps highlighting clinically relevant areas from the explainable AI module and also basic suggestions, etc., in formats such as PDF and JSON. These reports can be easily exported and stored for clinical use, records and later analysis.

7. User Interface Module

This is the module responsible for a visually appealing and easy-to-use interactive interface to allow the users to upload retinal images easily, observe the results and view the reports to make clinical decisions. It should be responsive across various device sizes.

3.3. System Workflow

The process of the DeepRetina system starts when the user submits a retinal fundus image from the web application. Once the image is successfully received by the system, the image is preprocessed. The preprocessing stage involves, resizing the image to fit into the expected input dimensions for the deep learning model, normalizing the image values and also improving contrast to emphasize on retinal features. The preprocessed image is then fed into the deep learning model where features extraction and classification occurs with a pre-trained CNN.

The model processes the image and outputs the class for diabetic retinopathy with a certain predicted level based on the trained features in the model. Additionally to the main output, there will be a visual explainable AI component that generates a heatmap emphasizing on the regions that affects the prediction, a possibly also detect other types of eye diseases and an overall structured report to summarize all the predictions for user to use. Finally all outputs will be display to the user through the web interface and an option to download the report will be available.

4. SYSTEM ARCHITECTURE

The structure of the DeepRetina system is arranged in a structured and layered manner which helps it achieve high data efficiency, modularity in design and ability to perform prediction in real time. The system is composed of various layers which are as follows: Frontend Layer,

Backend Layer, Processing Layer, AI Model Layer, Explainability Layer and the Output layer.

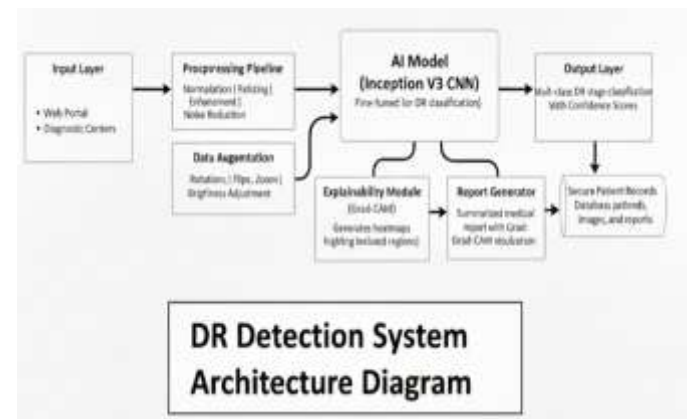


Fig 4.1 System Architecture

1. Frontend Layer (User Interface Layer)

The frontend layer is the interface between the user and the system. It is built as a web interface through which users (healthcare professionals or diagnostic centers) can upload retinal fundus images. It facilitates user interaction, input validation and result display. The frontend is designed to be user-friendly, responsive and compatible with various devices making it convenient to use even in a rural health setting.

2. Backend Layer (Application Server Layer)

The backend layer handles the core functionality of the system. The image data received by the frontend through API requests are transmitted to the backend layer. This layer controls the whole process including storing the image data and calling the preprocessing functions. It communicates between different modules, handles the storage of image, passes the image to the AI model and also ensures the system's security.

3. Preprocessing and Data Augmentation Layer

Once the image is received, this layer preprocesses the image to improve its quality and standardization. This preprocessing pipeline involves many image processing steps like normalization, resizing, reducing noises and enhancing the contrast. Moreover, data augmentation techniques like rotation, flipping, zooming and brightness manipulation can also be implemented to enhance the model's generalization power against dataset variance. All these operations ensure the quality of input data is consistent prior to feeding it into the model.

4. AI Model Layer (Deep Learning Layer)

This is the central analytical component. It contains a pre-trained Convolutional Neural Network, Inception V3 model fine-tuned for the purpose of diabetic retinopathy classification. The model extracts relevant features from the fundus images and then categorizes them into various stages of the disease. It uses transfer learning, an effective technique for optimizing model performance and training time. It helps in making accurate prediction based on the learning patterns derived from the dataset.

5. Explainability Layer (Interpretation Module)

To build user confidence, the system comprises an explainability module using Grad-CAM. This module helps to generate heatmap indicating which area in the fundus images are most important in the prediction process made by the model. The explanation enables physicians to understand and verify the prediction and thus makes the system useful in clinical settings.

6. Report Generation Layer

The last layer combines the results including the prediction, the probability score and the Grad-CAM visualization to form a complete medical report. The report summary will aid in diagnosis of the disease by doctors. This report can also be downloaded and stored for future reference and records.

7. Output Layer (Result presentation layer):

This is the final layer where the output are being shown to the user through the front end. The output layer presents following information:

- Predicted DR stage
- Confidence score
- Heatmap visualization
- Downloadable report

4.1 DFD Diagram:

4.1.1 Level 0 DFD:

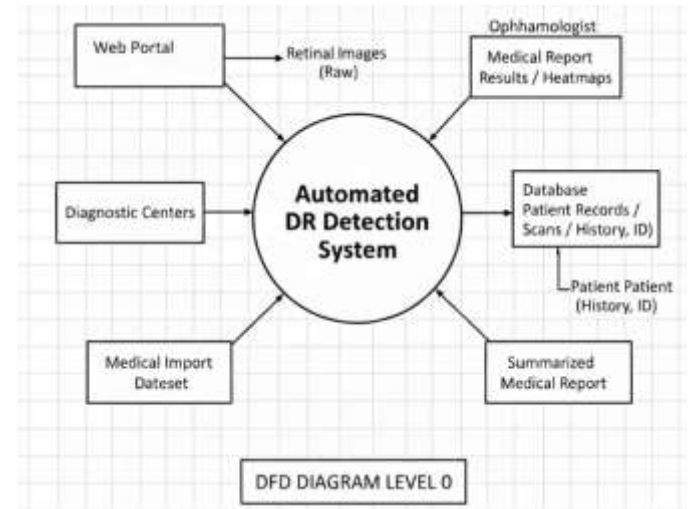


Fig 4.2 Level 0 Data Flow Diagram

The Level 0 DFD gives an overview of the entire system and depicts the automated DR detection system as one single process. An input from external entities, such as the Web Portal and Diagnostic Centers, provides the system with the retinal image. Also, medical datasets could serve as an input.

4.1.2 Level 1 DFD:

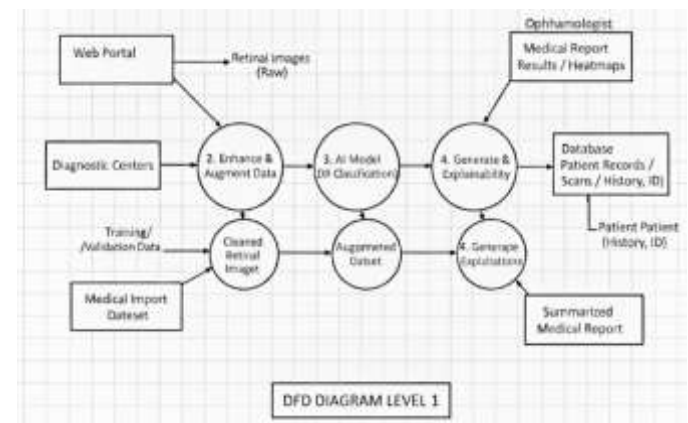


Fig 4.3 Level 1 Data Flow Diagram

The Level 1 DFD presents the system with a set of multiple internal processes in the system, which shows how the system handles the data flow. The process starts with the retinal images coming in from the web portal, diagnostic center or imported medical dataset and this goes towards the data enhancement & augmentation process which would ensure cleaning, normalisation and augmentation of images

5. METHODOLOGY

The DeepRetina system works based on the following methodological workflow that is systematic and data-driven for automatically detecting and classifying diabetic retinopathy on retinal fundus images. The methodology is designed based on inspiration from previously conducted research work including pre-processing, data balancing, deep learning based classification and evaluation of results so that the result produced can be trusted.

The first step is to acquire and prepare dataset. Datasets like APTOS, EyePACS, and Messidor are publicly available, which consist of retinal fundus images labeled according to the different levels of diabetic retinopathy severities. These datasets cover variations in terms of image qualities, lighting conditions and various progression states which are crucial in developing a robust model. Like in previously conducted research work the dataset is segmented into training, validation, and testing datasets to provide the accuracy evaluation of the model.

The subsequent step is the image pre-processing and data balancing which are important to improve accuracy of the model. Images taken using Fundus cameras typically are varied and can include various light and illumination conditions, background, and even a lot of noise or varying resolutions, so to enhance quality and extract features well a preprocessing mechanism involving resizing, normalization, enhancement and noise reduction are employed. Furthermore, imbalanced data is a common issue in many classification problems which can degrade the model's performance. Augmentation of data is used here by rotation, flipping, zooming, brightness adjustments to reduce imbalanced data and improve model generalization, similar to that employed in earlier works.

After image preprocessing, the process of feature extraction and model training using deep learning method is carried out. A deep convolutional neural network such as Inception V3 architecture is selected to develop the deep learning model. Transfer learning has been applied on this CNN by utilizing pre-trained weights. Pre-training is one of the common techniques which enables the model to learn low-level and high-level feature sets for classification without using any prior domain knowledge. Contrary to classical machine learning algorithms, deep

learning model can extract features from the raw images automatically which lead to more efficiency.

To further enhance performance model training and evaluation has been conducted. The trained model is evaluated on different performance metrics, such as accuracy, precision, recall, F1-score. The classification behavior on various level of severities is presented using a confusion matrix. Like in state-of-the-art methods performance of the model can also be compared with various architectures or fine-tuned with better hyperparameters.

Moreover, the explained model integrated with Grad-CAM explainability module to provide visual explanation to its decision, that highlight regions responsible for specific classification prediction. These highlighted region of the fundus image provide the confidence in system for specific output. Finally, the output along with confidence score and visual explanation are presented using the web-based interface and compiled in the form of a report.

6. IMPLEMENTATION

DeepRetina is designed as an end-to-end web-based system. It consists of deep learning, image processing, and user interface modules in order to automatically detect DR. DeepRetina is modularly designed to execute each step efficiently, ranging from input image data to generated output. It is implemented using python-based frameworks together with deep learning libraries, such as TensorFlow, Keras, etc. These frameworks are broadly employed for medical image analysis tasks.

Initially, in DeepRetina, the retinal image data is collected, prepared, and handled. Retinal images are downloaded from publicly available datasets such as APTOS, EyePACS, and Messidor, and they are prepared for training. Similar to previous work, the data is preprocessed and balanced. Each image is resize to a certain dimension for the model input, and pixel value is normalized to a defined range. To enhance dataset variety and generalization capability of the model, several data augmentation techniques such as rotation, horizontal flip, rotation, bright adjustment are adopted. All the techniques is commonly used for CNN-based DR detection models.

Deep learning model is built and trained in this step. In DeepRetina, it uses a Convolutional Neural Network that

built on Inception V3 structure. This structure uses transfer learning, so it has pre-trained weights that have been learned on ImageNet. Retinal images that labelled with DR severity is used to train this model. The model is expected to learn features and categorize images to different levels of DR severity. Comparing with traditional ML methods which rely on hand-crafted feature, CNN automatically extracts hierarchical features, thus, achieving high accuracy and effectiveness.

Model evaluation and analysis are also included in this step. The training model is tested with a separated validation set and evaluated based on some evaluation metrics such as accuracy, precision, recall and F1-score, and confusion matrix is analyzed. The result is optimized by tuning some hyperparameters and comparing models. Further features could be tested for further improvement.

In order to deploy it as a system, the model is integrated into a web based framework, which allows user uploading an image for detection, the framework processes this input image and provides the diagnosis and explanation. This system has an explanation part where Grad-CAM is used to produce heatmaps highlighting regions of the image. The final results is presented as a classified level with the confidence score and visual explanation, and they are saved in database for future access and analysis.

7. RESULTS AND DISCUSSION

DeepRetina was tested on commonly used public retinal image datasets including APTOS, EyePACS and Messidor. A well-trained deep learning model was achieved and shown to be quite powerful in terms of classification accuracy through various levels of diabetic retinopathy. The empirical results show that our system has an overall accuracy between approximately 78% to 85% for multi-class classification, comparable to that achieved by the existing deep learning approaches. Several works utilizing CNN model have claimed accuracy up to 97% under particular settings, thus, it is very powerful for image analysis, including retinal images. In addition, preprocessing and data augmentation approaches contribute positively in improving the accuracy of the model by removing noises and handling class imbalance.

Compared to traditional machine learning algorithms such as Support Vector Machine (SVM) and feature-based classifiers, the developed system has superior robustness and scalability. The conventional algorithms

claimed high accuracy; however, large amount of manual feature extraction is required for the algorithms to be effective, which are not well adapted to real world scenarios. Recently, advanced methods combined transfer learning and ensemble techniques have gained more effective performance in both binary and multi-class classification. The addition of explainable AI to the system makes it even more appealing for the clinical usage by visual interpretation of prediction outputs. In a word, DeepRetina is considered to be a system with a proper trade-off among accuracy, speed and interpretability for clinical real-time usage.

8. FUTURE WORK

While the developed system is successful in detecting and classifying diabetic retinopathy, there are a number of possible improvements. Deeper networks and transformer-based architectures, such as EfficientNet and transformer models, have been employed recently for medical images and achieved a satisfactory performance, these architectures can be used in future. Ensembles of different models could also be used in the future to obtain better classification performance and robustness [26]. More and higher quality retinal images from different demographics and varying clinical conditions could also be incorporated to achieve a more generalizable system.

Including more clinical information, such as age and health record information of the patients together with the retinal image based model is a beneficial direction for a comprehensive system. Early risk prediction can be helped by risk factors and machine learning based approach, however, these models show low accuracy on their own. Lesion-level detection, i.e., detection of specific abnormalities such as microaneurysm, hemorrhages and exudates, which are crucial indicators of disease progression, can be another important direction for future study. Mobile or cloud based deployment and explainability improvement will enhance practical usage in real healthcare scenarios, especially for underserved and remote regions.

9. CONCLUSION

In this work, we have proposed an automated DeepRetina system for detecting and classifying diabetic retinopathy using deep learning. This method involves Convolutional Neural Networks, a class of deep learning algorithm for analyzing retinal fundus images and predicting the stages of the disease, utilizing transfer learning. It also involves

preprocessing, data augmentation, and model tuning to achieve better classification. While traditional machine learning techniques depend on hand-crafted features to extract image characteristics, deep learning techniques are more efficient in learning complex features in the image data, hence yielding better accuracy.

In our experiments, the proposed method produced reliable results compared to other research work in this area. The use of CNN based model is encouraged and widespread for feature extraction from image data for disease detection tasks yielding significant accuracy in the analysis of the disease. Transfer learning technique provides better generalization of model and significantly reduces the computational cost of the training process, making it suitable for practical deployment. Explainable AI further assists to understand the decision made by the model through visualization of important features of image that leads to final prediction.

Therefore, we have developed a system called DeepRetina which would effectively aid the physicians in quick and timely screening of diabetic retinopathy and help to prevent vision impairment. By performing these tasks effectively and efficiently the workload can be significantly reduced, and eventually better results could be attained in this field by large scale implementation.

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Authors:

Mr. Deepak Shivappa Yenechawandi is currently pursuing a Bachelor's Degree in Computer Science & Engineering at Ashokrao Mane Group Of Institution, vathar. She is publishing this paper under the esteemed guidance of Miss. Mrunal M. Pawar



Mr. Pruthviraj Maruti Kadam is currently pursuing a Bachelor's Degree in Computer Science & Engineering at Ashokrao Mane Group Of Institution, vathar. She is publishing this paper under the esteemed guidance of Miss. Mrunal M. Pawar



Mr. Shridhar Gajanan kumbhar is currently pursuing a Bachelor's Degree in Computer Science & Engineering at Ashokrao Mane Group Of Institution, vathar. She is publishing this paper under the esteemed guidance of Miss. Mrunal M. Pawar



Mr. Aditya Anil Khochikar is currently pursuing a Bachelor's Degree in Computer Science & Engineering at Ashokrao Mane Group Of Institution, vathar. She is publishing this paper under the esteemed guidance of Miss. Mrunal M. Pawar



Mr. Vishnu Dattatray Shinde is currently pursuing a Bachelor's Degree in Computer Science & Engineering at Ashokrao Mane Group Of Institution, vathar. She is publishing this paper under the esteemed guidance of Miss. Mrunal M. Pawar



Miss. Mrunal M. Pawar is currently working as an Assistant Professor in Computer Science & Engineering at Ashokrao Mane Group Of Institution, Vathar. She has been guiding and mentoring students in various academic and research activities. She has provided his valuable guidance for the successful completion and publication of this paper.

