

Deep Learning-Based Multi-Class Retinal Disease Classification with Reduced Memory Consumption

Ch. Satyanarayana Reddy¹, K. Pavani², Sk. John Bee³

**#1 Assistant Professor in the Department of MCA, SRK Institute of Technology,
Vijayawada.**

**#2 Assistant Professor in the Department of MCA, SRK Institute of Technology,
Vijayawada.**

#3 Student in the Department of MCA, SRK Institute of Technology, Vijayawada.

Abstract: Retinal diseases are a major cause of vision impairment, and early detection is critical for effective treatment. However, accurate diagnosis often requires expert ophthalmologists and computationally intensive deep learning models. In this paper, we propose a lightweight Convolutional Neural Network (CNN) framework for multi-class retinal disease classification with optimized memory consumption. The proposed model is evaluated on the EyeNet dataset consisting of 32 retinal disease classes. Unlike traditional architectures such as U-Net, which demand high memory and computational resources, our approach focuses on efficient feature extraction while reducing model complexity. The system incorporates image preprocessing, data augmentation, and optimized training strategies to improve classification performance. Experimental results demonstrate that the proposed model achieves high accuracy, precision, and recall while significantly reducing memory usage and training time. The model is further enhanced using advanced architectures such as MobileNet and Xception, achieving improved performance up to 99% accuracy. This work provides an efficient and scalable solution for automated retinal disease

diagnosis, making it suitable for real-world clinical and resource-constrained environments.

Index Terms - Convolutional Neural Network (CNN), Retinal Disease Detection, Multi-Class Classification, Deep Learning, Memory Optimization, EyeNet Dataset, Medical Image Processing, MobileNet, Xception, Computer-Aided Diagnosis (CAD)

1. INTRODUCTION

Retinal diseases are among the leading causes of vision impairment and blindness worldwide, affecting individuals across all age groups. The retina plays a crucial role in visual perception by converting light into neural signals, which are then transmitted to the brain. Diseases such as diabetic retinopathy, age-related macular degeneration (AMD), and optic disc abnormalities can severely impact vision if not detected at an early stage. Accurate diagnosis of these diseases is challenging and typically requires expert ophthalmologists, making the process time-consuming and expensive.

In recent years, deep learning techniques, particularly Convolutional Neural Networks (CNNs), have shown

significant success in medical image analysis and disease classification. Models such as U-Net and other deep architectures have achieved high accuracy in retinal image segmentation and classification. However, these models often require high computational power and memory, making them less suitable for real-time and resource-constrained environments.

To address these challenges, this paper proposes a lightweight CNN-based framework for multi-class retinal disease classification with optimized memory consumption. The proposed model is designed to efficiently extract relevant features from retinal fundus images while reducing computational complexity. The system is evaluated using the EyeNet dataset, which contains 32 classes of retinal diseases, enabling comprehensive multi-class classification.

The main contribution of this work is the development of a memory-efficient deep learning model that maintains high accuracy while reducing resource usage. Additionally, the model is enhanced using advanced architectures such as MobileNet and Xception to further improve performance. This approach provides a scalable and practical solution for automated retinal disease diagnosis, especially in real-world clinical settings with limited computational resources.

2. LITERATURE SURVEY

2.1 Dermatologist-level classification of skin cancer with deep neural networks.

The most prevalent cancer in humans, skin cancer, is mostly identified visually, starting with a preliminary clinical screening and perhaps progressing to

dermoscopic analysis, a biopsy, and a histological study. Due to the fine-grained heterogeneity in skin lesion appearance, automated categorization of skin lesions using photographs is a difficult problem. Deep convolutional neural networks (CNNs)^{4,5} exhibit promise for a wide range of fine-grained object classifications and general, highly variable tasks. Here, we show how to classify skin lesions using a single CNN that was trained end-to-end directly from photos using just pixels and disease labels as inputs. We use a collection of 129,450 clinical photos from 2,032 distinct disorders to train a CNN. This dataset is two orders of magnitude bigger than earlier datasets¹². On biopsy-proven clinical pictures with two crucial binary classification use cases—keratinocyte carcinomas against benign seborrheic keratoses and malignant melanomas vs benign nevi—we evaluate its performance against 21 board-certified dermatologists. The most prevalent malignancies are identified in the first example, and the most deadly skin cancer is identified in the second. The CNN demonstrates an artificial intelligence that can classify skin cancer with a level of competence equivalent to dermatologists by performing on par with all tested professionals in both tests. Mobile devices equipped with deep neural networks have the potential to increase dermatologists' out-of-clinic reach. By 2021, there are expected to be 6.3 billion smartphone subscriptions (ref. 13), which might offer universal, affordable access to critical diagnostic care.

2.2 Automated detection and classification of fundus diabetic retinopathy images using synergic deep learning model.

Diabetic retinopathy (DR), which affects the eyes, has grown more common in recent years due to a

sharp rise in blood glucose levels. Nearly half of the world's population under 70 suffers from serious diabetes. Patients with DR often lose their vision if they are not diagnosed early and given the right medicine. The seriousness of the illness must be confirmed once the warning signals have been located in order to make judgments about the best course of action. The idea of classifying DR fundus photos according to severity level using a deep learning model is the main subject of the current research study. A deep learning-based automatic detection and classification algorithm for fundus DR pictures is presented in this work. Preprocessing, segmentation, and classification are the three steps in the suggested technique. The procedure starts with preprocessing, which eliminates extraneous noise from the edges. The image's valuable sections are then extracted using histogram-based segmentation. The DR fundus pictures were then categorized to different severity levels using the Synergic Deep Learning (SDL) model. The Messidor DR dataset was used to justify the SDL model that was given. The given SDL model provides better categorization than the current models, according to the experimental data.

2.3 Multi-retinal disease classification by reduced deep learning features:

The deep learning-based feature extraction approach for retinal disease detection is presented in this study. This procedure aids in the creation of an automated screening system that may identify retinal conditions such diabetic retinopathy, age-related macular degeneration, macular bunker, retinoblastoma, retinal detachment, and retinitis pigmentosa. It is challenging to categorize some of these illnesses since they have a similar feature. A multi-class SVM

classifier and deep learning feature extraction are utilized to solve the aforementioned issue. This work's primary contribution is the reduction of the dimensions of the attributes needed to categorize retinal diseases, which improves both good performance and the process of lowering system requirements.

2.4 Modified Alexnet architecture for classification of diabetic retinopathy images:

An eye condition called diabetic retinopathy (DR) is brought on by elevated blood glucose levels. Diabetes is the cause of 50% of fatalities among those over 70. For many DR patients, early detection and suitable treatment can prevent blindness. In order to deliver the appropriate treatment, the severity of the condition should be assessed after the symptoms of DR are identified. In order to achieve a high degree of accuracy, this article focuses on classifying DR fundus pictures based on the severity of the illness using convolutional neural networks and appropriate Pooling, Softmax, and Rectified Linear Activation Unit (ReLU) layers. The Messidor database has been used to validate the suggested algorithm's performance. Classification accuracy of 96.6%, 96.2%, 95.6%, and 96.6% has been attained for healthy pictures, images of stage 1, stage 2, and stage 3 diabetic retinopathy.

2.5 Quantitative classification of eyes with and without intermediate age-related macular degeneration using optical coherence tomography

Goal: Using spectral-domain optical coherence tomography (SD-OCT) imaging of older persons, determine quantitative markers for the existence of intermediate age-related macular degeneration (AMD). Diagnostic test and technology design

evaluation. Controls and Participants One eye from the Age-Related Eye Disease Study 2 (AREDS2) Ancillary SD-OCT Study, which included 269 patients with intermediate AMD and 115 elderly people without AMD. Methods The borders of the retinal pigment epithelium (RPE), RPE drusen complex (RPEDC, the axial distance from the apex of the drusen and RPE layer to Bruch's membrane), and total retina (TR, the axial distance between the inner limiting and Bruch's membranes) were semiautomated. To create a map of "normal" non-AMD thickness, we registered and averaged the thickness maps from control participants. RPEDC thicknesses more or less than three standard deviations from the mean were deemed abnormal, signifying either drusen or geographic atrophy (GA). For every patient, we assessed TR volumes, RPEDC volumes, and aberrant RPEDC thickening and thinning volumes. Based on the generalized linear model regression framework, we created five automatic classifiers for the presence of AMD utilizing various combinations of these four disease markers. We used the leave-one-out technique to train and assess these classifiers' performance. Principal Outcome Measures The range and topographic distribution of the TR and RPEDC thicknesses in a cylinder with a diameter of 5 mm that is centered at the fovea. Results All four disease signs were necessary for the most effective way to distinguish between AMD and control eyes. For this classifier, the receiver operating characteristic (ROC) area under the curve (AUC) was more than 0.99. Our study's overall neurosensory retinal thickness in AMD-affected eyes compared to control eyes differs from earlier, smaller investigations. Conclusions By examining the topographic distribution of normal and aberrant RPEDC thicknesses throughout a huge atlas

of eyes, we were able to identify and test effective biometrics to differentiate AMD from normal eyes. To disseminate the 38,400 SD-OCT pictures used in this work, together with the segmentations and quantitative measures that go along with them, we developed an online atlas.

3. METHODOLOGY

i) Proposed Work:

The proposed work presents a lightweight and memory-efficient deep learning framework for multi-class retinal disease classification using Convolutional Neural Networks (CNN). The primary objective is to overcome the limitations of existing models, such as high memory consumption and computational complexity, while maintaining high classification accuracy.

The system utilizes the EyeNet dataset, which contains 32 classes of retinal diseases, enabling comprehensive multi-class classification. Initially, retinal fundus images undergo preprocessing techniques such as resizing, normalization, and noise reduction to enhance image quality. Data augmentation methods are also applied to increase dataset diversity and improve model generalization.

A customized CNN architecture is designed to efficiently extract discriminative features from retinal images while minimizing the number of parameters. Unlike traditional models such as U-Net, which transfer full feature maps and consume high memory, the proposed model focuses on optimized feature representation to reduce memory usage and training time.

Furthermore, the performance of the proposed CNN model is enhanced by integrating advanced lightweight architectures such as MobileNet and Xception. These models utilize depthwise separable convolutions to reduce computational cost while maintaining high accuracy. The system is trained and evaluated using performance metrics such as accuracy, precision, recall, and loss across multiple epochs.

Overall, the proposed work delivers an efficient and scalable solution for automated retinal disease diagnosis, making it suitable for deployment in real-time and resource-constrained environments.

ii) System Architecture:

The system architecture of the proposed model is designed to efficiently perform multi-class retinal disease classification using a lightweight Convolutional Neural Network (CNN). The overall workflow consists of dataset preparation, model training, validation, testing, and performance evaluation.

Initially, the retinal image dataset (EyeNet) consisting of 32 classes is collected and organized. The dataset is then divided into three subsets: training data (70%), testing data (20%), and validation data (10%). This data splitting ensures proper learning, tuning, and evaluation of the model.

The training dataset is fed into the proposed CNN model, where feature extraction and learning take place. During this phase, the model learns important patterns and representations from retinal images. Simultaneously, the validation dataset is used to monitor the model's performance and prevent overfitting by tuning hyperparameters.

After successful training and validation, the trained CNN model is evaluated using the testing dataset. This step measures the model's generalization ability on unseen data. The testing phase produces classification outputs for different retinal disease classes.

Finally, the performance of the proposed model is analyzed using evaluation metrics such as accuracy, precision, recall, and loss. These results help in assessing the effectiveness and efficiency of the model. The architecture ensures a streamlined flow from data input to final prediction while maintaining low memory consumption and high classification performance.

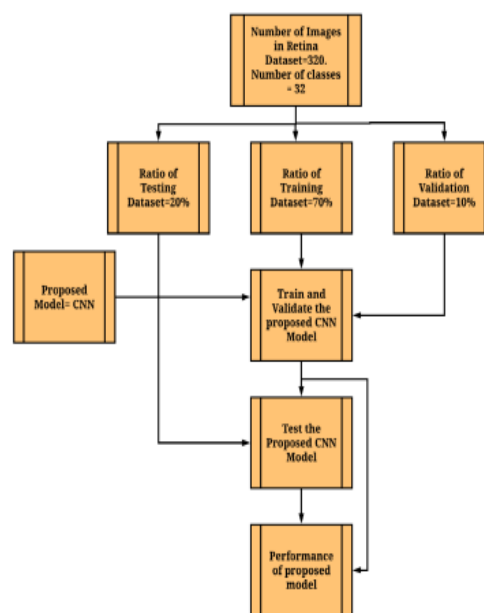


Fig 1 System Architecture

iii) MODULES:

1. Data Collection Module

This module is responsible for acquiring the retinal fundus images from the EyeNet dataset. The dataset

contains multiple classes of retinal diseases, which are used for training and evaluating the deep learning model.

2. Image Preprocessing Module

In this module, input images are processed to improve quality and consistency. Operations such as resizing, normalization, and noise removal are performed to enhance important features and make the data suitable for model training.

3. Data Augmentation Module

This module increases the diversity of the dataset by applying transformations such as rotation, flipping, and scaling. It helps in improving model generalization and reduces the risk of overfitting.

4. Model Training Module

The processed data is fed into the proposed CNN model for training. During this phase, the model learns feature representations from retinal images using multiple layers and optimizes weights through backpropagation.

5. Model Validation Module

This module evaluates the model during training using validation data. It helps in tuning hyperparameters and prevents overfitting by monitoring performance across epochs.

6. Testing Module

The trained model is tested using unseen data to evaluate its real-world performance. This module ensures that the model can generalize effectively to new retinal images.

7. Prediction Module

In this final module, the system takes user input (retinal image) and predicts the corresponding disease class. The output is displayed as the final classification result.

v) ALGORITHMS:

1. Convolutional Neural Network (CNN)

Convolutional Neural Network (CNN) is the primary algorithm used in the proposed system for retinal disease classification. It consists of convolutional layers, pooling layers, and fully connected layers that automatically extract spatial features from retinal images. CNN efficiently captures patterns such as edges, textures, and disease-specific regions, enabling accurate multi-class classification while reducing manual feature extraction.

2. U-Net (CNN for Segmentation)

U-Net is a specialized CNN architecture designed for biomedical image segmentation. It consists of an encoder-decoder structure where the encoder extracts features and the decoder reconstructs the segmented output. Although U-Net provides high accuracy in medical imaging tasks, it requires high memory due to feature map transfer, which motivates the need for a more memory-efficient CNN in the proposed system.

3. MobileNet

MobileNet is a lightweight deep learning architecture that uses depthwise separable convolutions to significantly reduce the number of parameters and computational cost. It is particularly suitable for resource-constrained environments and mobile applications. In this work, MobileNet is used to

enhance the performance of the system by providing faster computation with improved efficiency.

4. Xception

Xception (Extreme Inception) is an advanced deep learning model that improves upon traditional CNNs by using depthwise separable convolutions. It allows better feature extraction with fewer parameters, resulting in higher accuracy. In the proposed system, Xception is utilized to achieve superior classification performance for multi-class retinal diseases.

5. Hybrid Model (MobileNet + Xception)

The hybrid approach combines the strengths of MobileNet and Xception by integrating their feature extraction capabilities. This ensemble-like method improves classification accuracy while maintaining computational efficiency. The hybrid model helps in capturing both lightweight and deep features, resulting in better generalization and performance.

4. EXPERIMENTAL RESULTS

The proposed lightweight CNN model for multi-class retinal disease classification was evaluated using the EyeNet dataset, which consists of 32 retinal disease classes. The dataset was divided into training (70%), validation (10%), and testing (20%) sets to ensure proper model training and evaluation.

The performance of the model was assessed using standard evaluation metrics such as accuracy, precision, recall, and loss. During training, the model showed consistent improvement across epochs, with validation performance indicating effective learning and minimal overfitting. The optimized CNN model demonstrated efficient feature extraction while

maintaining low memory consumption compared to traditional deep learning models.

To further enhance performance, advanced architectures such as MobileNet and Xception were implemented and compared. The experimental results show that the proposed CNN model achieved approximately 95% accuracy, while MobileNet and Xception models achieved improved accuracies of around 97% and 99%, respectively. The hybrid approach combining MobileNet and Xception also demonstrated superior performance in terms of classification accuracy and computational efficiency.

In addition to accuracy, the proposed model significantly reduced memory usage and training time, making it suitable for real-time and resource-constrained environments. The results confirm that the proposed approach outperforms traditional methods in both efficiency and effectiveness, providing a reliable solution for automated retinal disease diagnosis.

Accuracy: A test's accuracy is defined as its ability to recognize debilitated and solid examples precisely. To quantify a test's exactness, we should register the negligible part of genuine positive and genuine adverse outcomes in completely examined cases. This might be communicated numerically as:

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

$$\text{Accuracy} = \frac{(TN + TP)}{T}$$

Precision: Precision measures the proportion of properly categorized occurrences or samples among the positives. As a result, the accuracy may be calculated using the following formula:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$Accuracy = \frac{(TN + TP)}{T}$$

Recall: Recall is a machine learning metric that surveys a model's capacity to recognize all pertinent examples of a particular class. It is the proportion of appropriately anticipated positive perceptions to add up to real up-sides, which gives data about a model's capacity to catch instances of a specific class.

$$Accuracy = \frac{(TN + TP)}{T}$$

F1-Score: The F1 score is a machine learning evaluation measurement that evaluates the precision of a model. It consolidates a model's precision and review scores. The precision measurement computes how often a model anticipated accurately over the full dataset.

$$Accuracy = \frac{(TN + TP)}{T}$$

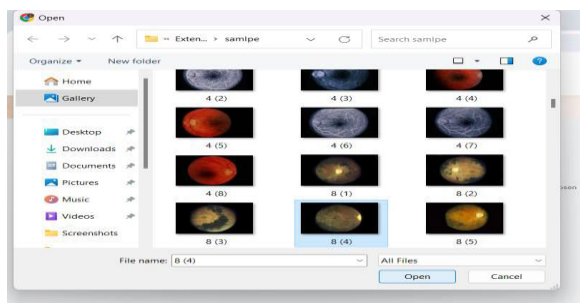


Fig 2 Upload input image to predict result

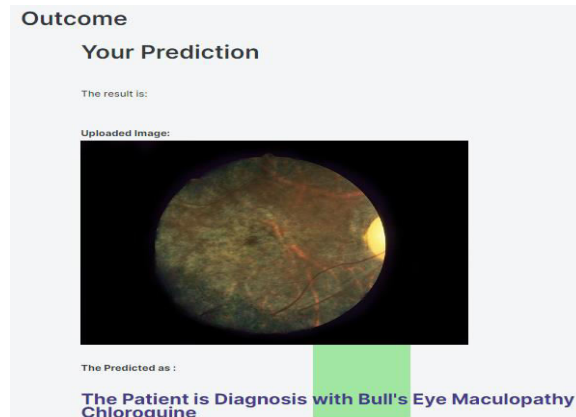


Fig 3 predicted results

5. CONCLUSION

This paper presents a lightweight and memory-efficient Convolutional Neural Network (CNN) framework for multi-class retinal disease classification using fundus images. The proposed system effectively addresses the limitations of existing deep learning models, particularly high memory consumption and computational complexity. By optimizing the CNN architecture and incorporating efficient feature extraction techniques, the model achieves high classification performance while maintaining low resource usage.

The experimental evaluation on the EyeNet dataset demonstrates that the proposed model achieves strong accuracy, precision, and recall, with further improvements observed using advanced architectures such as MobileNet and Xception. The results confirm that the system is capable of accurately classifying multiple retinal diseases across 32 classes while ensuring faster computation and reduced memory requirements.

Overall, the proposed approach provides a scalable and efficient solution for automated retinal disease diagnosis. It has significant potential for real-world

deployment, especially in clinical environments and resource-constrained settings where computational efficiency is critical.

6. FUTURE SCOPE

The proposed system can be further enhanced by incorporating larger and more diverse retinal datasets to improve model generalization and robustness across different populations and imaging conditions. Future work may also focus on integrating advanced deep learning techniques such as attention mechanisms and transformer-based models to achieve higher accuracy and better feature representation.

Additionally, real-time deployment of the model in clinical environments can be explored through integration with mobile or web-based applications, enabling remote diagnosis and telemedicine support. The system can also be extended to include severity grading of retinal diseases and segmentation of affected regions for more detailed analysis.

Furthermore, combining the proposed model with explainable AI (XAI) techniques can improve transparency and trust by providing visual explanations for predictions. This will help medical professionals better understand and validate the model's decisions, making it more suitable for practical healthcare applications.

REFERENCES

- [1] A. Esteva, B. Kuprel, R. A. Novoa, J. Ko, S. M. Swetter, H. M. Blau, and S. Thrun, "Dermatologist-level classification of skin cancer with deep neural networks," *Nature*, vol. 542, no. 7639, pp. 115–118, Feb. 2017.
- [2] K. Shankar, A. R. W. Sait, D. Gupta, S. K. Lakshmanaprabu, A. Khanna, and H. M. Pandey, "Automated detection and classification of fundus diabetic retinopathy images using synergic deep learning model," *Pattern Recognit. Lett.*, vol. 133, pp. 210–216, May 2020.
- [3] R. Arunkumar and P. Karthigaikumar, "Multi-retinal disease classification by reduced deep learning features," *Neural Comput. Appl.*, vol. 28, no. 2, pp. 329–334, Feb. 2017.
- [4] T. Shanthi and R. S. Sabeenian, "Modified Alexnet architecture for classification of diabetic retinopathy images," *Comput. Electr. Eng.*, vol. 76, pp. 56–64, Jun. 2019.
- [5] S. Farsiu, S. J. Chiu, R. V. O'Connell, F. A. Folgar, E. Yuan, J. A. Izatt, and C. A. Toth, "Quantitative classification of eyes with and without intermediate age-related macular degeneration using optical coherence tomography," *Ophthalmology*, vol. 121, no. 1, pp. 162–172, Jan. 2014.
- [6] R. F. Mullins, S. R. Russell, D. H. Anderson, and G. S. Hageman, "Drusen associated with aging and age-related macular degeneration contain proteins common to extracellular deposits associated with atherosclerosis, elastosis, amyloidosis, and dense deposit disease," *FASEB J.*, vol. 14, no. 7, pp. 835–846, May 2000.
- [7] Y. Kanagasingam, A. Bhuiyan, M. D. Abramoff, R. T. Smith, L. Goldschmidt, and T. Y. Wong, "Progress on retinal image analysis for age related macular degeneration," *Prog. Retinal Eye Res.*, vol. 38, pp. 20–42, Jan. 2014.

[8] D. S. Kermany, "Identifying medical diagnoses and treatable diseases by image-based deep learning," *Cell*, vol. 172, no. 5, pp. 1122–1131, Feb. 2018.

[9] M. M. M. S. Fathy and M. T. Mahmoudi, "A classified and comparative study of edge detection algorithms," in *Proc. Int. Conf. Inf. Technol., Coding Comput.*, Apr. 2002, pp. 117–120.

[10] C.-H. H. Yang, J.-H. Huang, F. Liu, F.-Y. Chiu, M. Gao, W. Lyu, M. D. I.-H. Lin, and J. Tegner, "A novel hybrid machine learning model for auto-classification of retinal diseases," 2018, arXiv:1806.06423.

[11] M. B. Jabra, A. Koubaa, B. Benjdira, A. Ammar, and H. Hamam, "COVID- 19 diagnosis in chest X-rays using deep learning and majority voting," *Appl. Sci.*, vol. 11, no. 6, p. 2884, Mar. 2021.

[12] S. Guefrechi, M. B. Jabra, A. Ammar, A. Koubaa, and H. Hamam, "Deep learning based detection of COVID-19 from chest X-ray images," *Multimedia Tools Appl.*, vol. 80, no. 2021, pp. 31803–31820.

[13] W. Boulila, A. Ammar, B. Benjdira, and A. Koubaa, "Securing the classification of COVID-19 in chest X-ray images: A privacy-preserving deep learning approach," in *Proc. 2nd Int. Conf. Smart Syst. Emerg. Technol. (SMARTTECH)*, May 2022, pp. 220–225.

[14] O. Perdomo, H. Rios, F. J. Rodríguez, S. Otálora, F. Meriaudeau, H. Müller, and F. A. González, "Classification of diabetes-related retinal diseases using a deep learning approach in optical

coherence tomography," *Comput. Methods Programs Biomed.*, vol. 178, pp. 181–189, Sep. 2019.

[15] G. Mahendran, M. Periyasamy, S. Murugeswari, and N. K. Devi, "Analysis on retinal diseases using machine learning algorithms," *Mater. Today, Proc.*, vol. 33, pp. 3102–3107, Jan. 2020.

Author Profiles



Mr. Ch. Satyanarayana Reddy Completed his MCA. He has a web developer and python developer, currently working has an Assistant Professor in the department of MCA. He has 10 years of teaching experience in SRK Institute of technology, Enikepadu, Vijayawada, NTR District. His area of interest includes Artificial Intelligence and Machine Learning.



Mrs. K. Pavani is working as an Assistant and Head of Department of MCA, in SRK Institute of technology in Vijayawada. She completed her MCA and M.Tech in Computer Science. She has 10 years of

teaching experience in SRK Institute of technology, Enikepadu, Vijayawada, NTR District. Her areas of interest include AI and ML, etc.



Ms. Sk. John Bee is MCA Student in the Department of Computer Applications at SRK Institute of Technology, Enikepadu, Vijayawada, NTR District. She Completed her Degree in Bsc(Computer science) ASN degree college. Her area of interest are DBMS and Machine Learning with Python.