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ADEMNET architecture: An innovative solution for adaptive multi-class balancing problem in image classification

Neetha Papanna Umalakshmi[1], Simran Sathyanarayana[1], Pushpa Chicktotlikere Nagappa[1], Thriveni Javarappa[1], Venugopal Kuppanna Rajuk[2]
[1]Department of Computer Science and Engineering, University of Visvesvaraya College of Engineering, Bangalore, India
[2]Former Vice-Chancellor, Bangalore University, Bangalore, India

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ABSTRACT

In the field of medical image processing, achieving high performance in the classification of four types of dementia poses a significant challenge. This research presents a novel approach that outperforms existing methodologies, bringing about a transformative impact in this specialized domain. The method integrates the adaptive synthetic–nominal (ADASYN) technique with a DEMNET framework, resulting in a substantial performance improvement of 95.45% compared to current benchmarks. Through meticulous experimentation on a dementia dataset encompassing four distinct types, we consistently demonstrate significant enhancements achieved by the refined strategy. This innovation not only raises the performance standard but also provides a robust and adaptable solution that can be easily integrated into existing systems. The implications of this advancement open up new avenues for both research and practical applications. This work exemplifies the power of innovative approaches to push the limits of performance and establishes a new benchmark for excellence within this specific domain.

Corresponding Author:

Neetha Papanna Umalakshmi
Department of Computer Science and Engineering, University of Visvesvaraya College of Engineering
Bangalore, 560001, Karnataka, India
Email: neethapud@gmail.com

1. INTRODUCTION

Alzheimer's disease (AD) is the most common type of dementia, marked by a slow progression that begins with mild memory issues and can eventually lead to challenges in participating in meaningful conversations and responding to the environment [1], [2]. Dementia is marked by a deterioration in cognitive functions, encompassing aspects such as thought processes, memory, and logical reasoning, to an extent that significantly interferes with an individual's everyday tasks and routines [3]. The convergence of AD and dementia within the domain of medical data underscores a complex issue requiring innovative solutions. These neurodegenerative disorders, characterized by cognitive decline, memory loss, and diminished functionality, pose a substantial hurdle in the global healthcare landscape. The accurate diagnosis of AD and dementia is vital for enabling timely interventions, improving patient care, and deepening our understanding of disease progression.

Navigating the complexities of categorizing AD and dementia across various stages poses a significant challenge. A common issue encountered when constructing diagnostic models is the presence of Class Imbalance within the datasets. Other issue may be preprocessing the medical images [4]-[7]. This challenge arises due to an uneven distribution of data samples among different classes, resulting in insufficient data for critical categories. In the specific context of AD and dementia classification, this imbalance becomes a central hurdle. Given that the majority of samples originate from individuals without these conditions, those affected by AD and dementia represent the minority. Consequently, this imbalance detrimentally impacts the learning capabilities of both machine learning (ML) and deep learning (DL) models, leading to biased and suboptimal outcomes.

Our investigation is motivated by the imperative need to address the intricate challenges posed by AD and various forms of dementia within the domain of medical data. The urgency stems from the profound impact of these neurodegenerative conditions on individuals and their families. Moreover, the complexity involved in executing multi-class classification, requiring accurate differentiation among various subtypes of diseases, adds to the difficulty of this task.

The results achieved in binary classification tasks thus far have demonstrated promising performance. Table 1 presents a concise overview of a Binary classification outcomes. However, as we navigate the complexities of multi-class classification scenarios, particularly in the context of studies related to AD and dementia, the landscape becomes inherently intricate. The nuances introduced by different disease stages and subtypes present a formidable challenge to the models' ability to maintain their previously achieved levels of accuracy.

Raju and Rao [8], presented for colorectal multi-class image classification. But, the model worked with ten anonymized H&E stained colorectal cancer (CRC) tissue slides. Meanwhile, Foeady *et al.* [9], worked with Lung Cancer classifications using CT scans. Some research observes that the use of MRI considered bettering than CT scans. Similarly, Murugan *et al.* [10], works with six class classification task. But, the accuracy was noted as 90% in plant disease classification. Table 2 presents a concise overview of a multi-class classification outcomes in AD/dementia classification issue.

Table 1. Summary of the papers that worked with binary classification problem

Authors	Method	Dataset	Binary Class	Accuracy
Huanhuan *et al.* [11]	Ensemble Learning method	ADNI	AD/MCI MCI/NC	97.65% 88.37%
Ullanat *et al.* [12]	Residual 3-D CNN	ADNI	AD/NC	91.4% (without attention block) 91% (with attention block)
Jain *et al.* [13]	PF SE CT L	ADNI	AD/CN AD/MCI MCI/CN	99.14% 99.30% 99.22%
Mehmood *et al.* [14]	Transfer Learning	ADNI	AD/NC EMCI/LMCI	98.73% 83.72%
Shi *et al.* [15]	MM-SDPN	ADNI	AD/NC MCI/NC MCI-C/MCI-NC	96.93% 86.99% 76.52%
Janghel and Rathore [16]	VGG-16	ADNI	AD/Normal (fMRI) AD/Normal (PET)	99.95% 73.46%

Table 2. Summary of the papers that worked with multi-class classification

Authors	Method	Dataset	Multi-Class	Accuracy	Drawbacks
Murugan *et al.* [17]	DEMNET	Kaggle (Size 176 * 176)	MID/MOD/ND/VMD	95.23%	Accuracy is yet to increase
Raees and Thomas [18]	DNN	ADNI	MCI/AD/NC	80- 90%	For three-Class
Jain *et al.* [13]	PF SE CTL	ADNI	AD/Cognitively Normal/MCI	95.73%	For three-Class
Shi *et al.* [15]	MM-SDPN	ADNI	AD/MCI-C/MCI-NC/NC	55.34%	Accuracy is yet to increase
Neetha *et al.* [19]	D-DEMNET	ADNI	AD/lMCI/MCI/ eMCI/NC	95.16%	Comparatively, it is less effective in five class classification
Suganthe *et al.* [20]	Combination of Inception and ResNet V2	Kaggle	MID/MOD/ND/ VMD	79.12%	Accuracy is yet to increase

Motivated by the aim to bridge existing gaps, we propose an innovative approach that addresses both class imbalance and multi-class classification simultaneously. This research conducts an in-depth exploration of the nuanced interplay among AD, dementia, and the challenge of class imbalance within medical datasets. Furthermore, our investigation extends to delve into the intricacies of multi-class classification. Our objective is to enhance the accuracy [21] of AD and dementia diagnoses, with the potential for a paradigmatic change in disease categorization and improved patient outcomes. The contributions of the work include:

– Our study significantly advances disease classification methodologies across various medical scenarios by introducing a holistic solution called ADEMNET that effectively tackles both the issues of class imbalance and multi-class challenges.
– We introduce a novel methodology aimed at addressing the challenges associated with various forms of dementia, imbalances in class distribution within medical datasets, and the complexities of multi-class classification, all concurrently.
– Highlights all the possible results that are meant for evaluating classification model.
– Our investigation unveils noteworthy improvements in accuracy during the classification of stages of dementia.

The document is structured into multiple segments. In section 2, an in-depth discussion of the proposed model is presented, encompassing information about the dataset and the problem statement. Section 3 explores an assessment of the model's performance, making comparisons with the baseline model. Finally, section 4 provides a succinct summary of the model's achievements.

2. PROPOSED MODEL

2.1. Problem statement

Classifying AD/dementia across multiple classes in image datasets presents a dual challenge. This challenge involves accurately distinguishing between various stages and types of the disease while grappling with notable class imbalance within the dataset. If unaddressed, the Imbalance among classes can result in biased models that face difficulties in effectively generalizing across diverse instances. Hence, it is imperative to devise a solution that not only ensures accurate classification of disease across multiple classes but also addresses the impact of class imbalance to guarantee fair and comprehensive diagnostic outcomes.

2.2. Dataset description

In this study, we commenced our inquiry by acquiring established datasets, specifically the four-class dementia dataset sourced from Kaggle [22]. To facilitate thorough analysis, we performed essential preprocessing procedures to appropriately prepare the datasets. Subsequently, we addressed the observed challenge of Class Imbalance inherent in these datasets. These datasets encompass a total of 6,400 magnetic resonance (MR) images, classified into four categories: mild dementia (MID), non-dementia (ND), moderate dementia (MOD), and very mild dementia (VMD). Each image in the dataset resized to 64 * 64 pixels. Table 3 gives a dataset description.

Table 3. Dataset description

SL. No	Classes	No. of images
1.	Non-demented	2240
2.	Very mild demented	64
3.	Mild demented	896
4.	Moderate demented	3200

2.3. ADEMNET architecture-proposed architecture

Figure 1 illustrates the configuration of the architecture proposed in this research. Following data preprocessing, including tasks such as scaling and resizing to align with the architecture requirements, the processed images are fed into the framework. To address class imbalance, the input undergoes the adaptive synthetic–nominal (ADASYN) technique, as shown in Figure 1. Upon achieving a balanced dataset, the next step involves dataset splitting. This entails dividing the entire dataset into three subsets: test data, train data, and validate data, with a distribution ratio of 60:20:20. After splitting process, the model is trained using a layered architecture that includes convolutional, pooling, DEMNET blocks, dropout, flatten, and dense layers. The rectified linear unit (ReLU) acts as the activation function primarily employed in hidden layers [23]. Moreover, the proposed architecture incorporates the softmax layer for classification purposes. To evaluate the effectiveness of the suggested framework, we utilized metrics such as accuracy, F1-score, recall, and precision [24]. The optimizer used here is RMSProp [25]. Below steps show the summary of the process with architecture.

a) Data pre-processing: In this phase, critical data preparation tasks are undertaken, encompassing processes such as data cleansing, standardization, and extraction of pertinent features. These measures ensure that the input data is suitably organized for subsequent processing.
b) ADASYN for dataset balancing: Addressing class imbalance in AD/dementia classification is crucial. ADASYN proves to be an efficient method for alleviating class imbalance in image datasets. This technique tackles the issue by generating synthetic samples that adapt to the data distribution. Its adaptability is especially beneficial in scenarios where conventional oversampling methods may fall short of delivering optimal results.

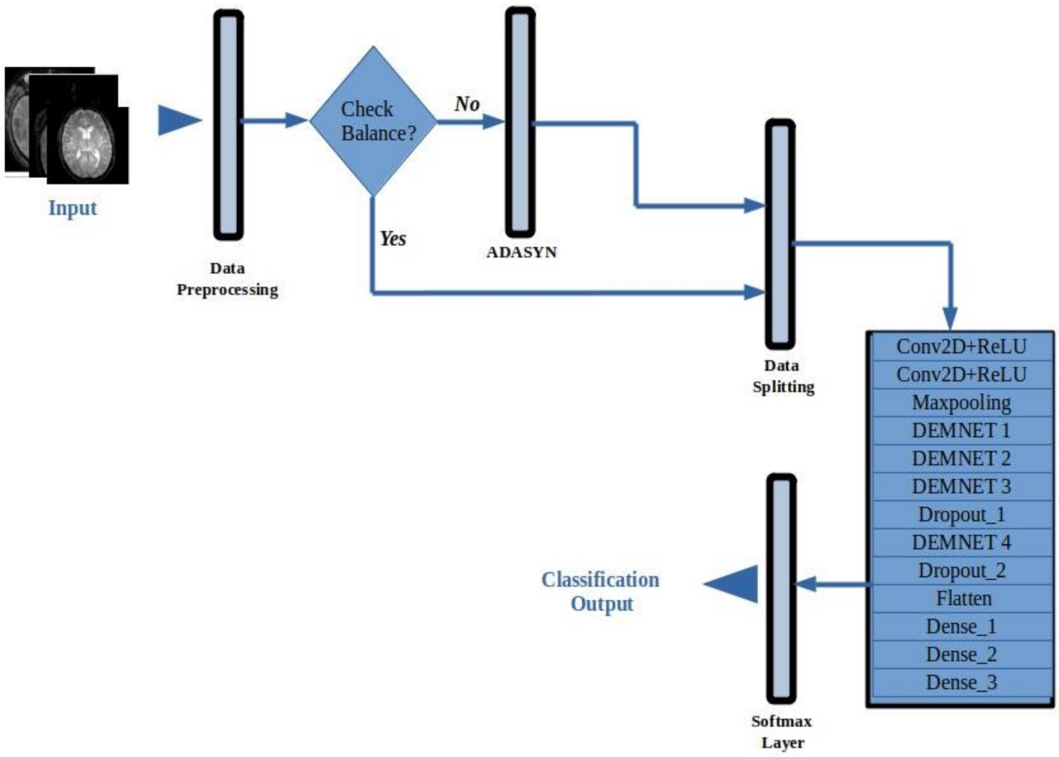

Figure 1. ADEMNET architecture

c) Data splitting: The datasets were divided into separate training, testing, and validation sets. This division allowed for a precise evaluation of the model's performance on data it had not encountered before.

d) Model training process: We employed a following layers in architecture:
- Convolution layer: The initial layers of the convolutional network extract information from the input image through the application of filters.
- Pooling layer: The main goal of this layer is to reduce computational costs by minimizing the spatial size of the image and the set of trainable features.
- DEMNET block: The DEMNET block consists of two consecutive convolutional layers employing ReLU activation, succeeded by a batch normalization layer and a subsequent maxpooling layer.
- Dropout layer: The dropout technique functions as a regularization method, emulating the training process of multiple neural networks concurrently, each featuring unique architectures.
- Dense layer: The dense layer, alternatively referred to as a fully connected layer, constitutes a neural network layer characterized by intricate interconnections between each neuron.
- Batch normalization layer: A traditional neural network is trained using batches of input data rather than individual inputs. Likewise, batch normalization operates on these batches, not individual inputs, with the aim of improving the speed and stability of neural networks.

Below represents the Algorithm 1 of the ADEMNET architecture. Leveraging the power of DL, it efficiently handles complex data, achieving a notable accuracy in distinguishing between different categories of dementia.

Algorithm 1: ADEMNET
```
Input: MRI images of Different Classes.
Output: Classification Results including Accuracy, Precision, Recall, and F1-Scores.
BEGIN:
1.      Step 1: Load the MRI data
2.                        Let D = {Non Demented, Very Mild Demented, Mild Demented, and
              Moderate Demented} represent the collected dataset classes.
3.      Step 2:  Data pre-processing of the MRI images
4.                        2.1 Perform Data Augmentation:
5.                Image Resize, Zoom, Brightness Range, Horz Flip and Rescaling.
6.                        2.2 Image Normalization:
7.                Perform Over-Sampling of the images using ADASYN, as the classes are
imbalanced.
```

```
            Store the re-sampled data to synthetic samples and synthetic labels.
            Concatenate the synthetic labels to augmented labels and synthetic samples
to augmented samples.
            Resize the pixels of the augmented images to size 64 * 64.
    Step 3: Apply Sequential()
                Building Model with ReLU as activation function.
                Apply categorical-cross entropy.
                RMSProp optimizer to train the model.
    Step 4: Pass each MRI image to the convolution process
                Process each image of dimensions 64 * 64 * 3 processed depth-wise
         separate convolutions and convert the image into dimensions.
                Drop Out the processed matrix/images by 0.5.
    Step 5: The image is converted/fattened into a single-dimensional array
            Step 6: Apply the Dense layer with the softmax activation function and
         then apply dropout by 0.5 to the resultant array
            Step 7: Repeat Step 6 with a different set of neurons, and apply dropout
         for repeated learning and activate the neurons
            Step 8: Plot the ACC, and AUC curves for the trained model
            Step 9: Apply confusion matrix, fetch the classification report results,
and calculate the accuracy for test data
  END
```

3. RESULTS AND DISCUSSIONS

3.1. Experimental setup

The colab pro service, which incorporates a Tesla P100-PCIE-16GB GPU, was utilized for the testing process in Windows 10. Model training consisted of 50 iterations, starting with an initial learning rate set at 0.001. The primary framework employed was TensorFlow version 2.7, with the implementation carried out in the Python language. Essential libraries such as Keras, Pandas, NumPy, and Matplotlib were also utilized during the experimentation.

3.2. DEMNET and ADEMNET applied to a four-class dataset

The methodology applied in this investigation involves the use of a four-class dataset, following the recommended procedures outlined for performance evaluation within that dataset. A comparative analysis is conducted between the currently leading model for classifying the four-class dataset [17] which is considered as a best in performance than compared with other state-of-the-models such as CNN as referred in Table 2, with the newly proposed ADEMNET architecture. We utilized both architectures on an identical four-class dataset. First, we created a baseline model with a minor adjustment, specifically resizing images to 64 * 64 pixels. Following that, we assessed the performance of the baseline model and contrasted it with the outcomes obtained using our proposed architecture, all while keeping the image dimension constant at 64 * 64 pixels. Proposed methodology integrates the ADASYN technique into the architecture, yielding a validation accuracy of 95.45% and an overall training accuracy of 99.65%. Evaluation of the models post-training involves a separate test set with previously unseen images. Figure 2 shows the training and validation curves of the architecture with comparion with base model. Figure 3 presents the confusion matrix generated by the ADEMNET architecture, detailing expected class labels alongside assigned labels for the four distinct dementia types.

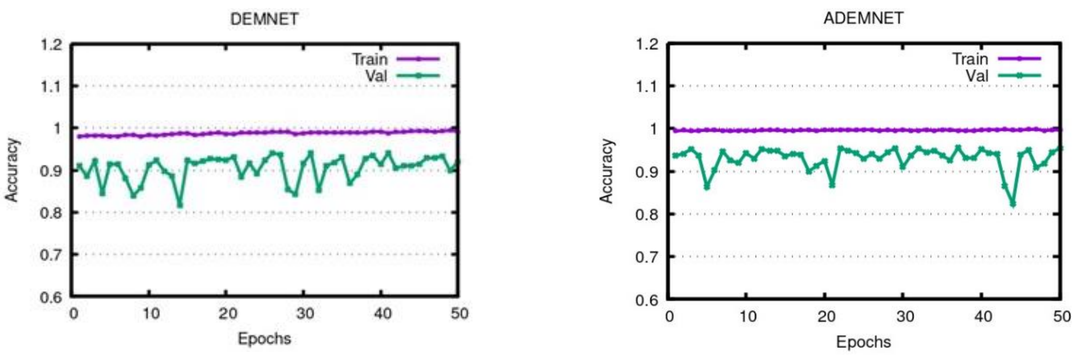

Figure 2. Creating training and validation curves for the DEMNET and ADEMNET architectures to evaluate accuracy

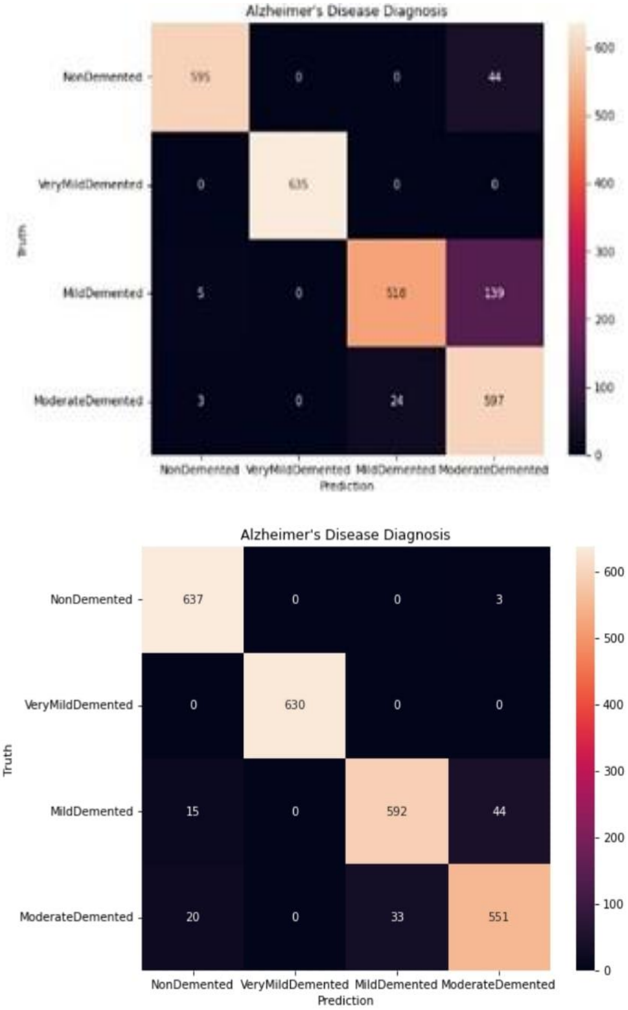

Figure 3. An evaluation of confusion matrix disparities between two unique architectures

The evaluation metrics, encompassing recall, precision, and F1-score, demonstrate promising results for specific classes, as illustrated in Figure 4, with corresponding values detailed in Table 4. Notably, the ADEMNET architecture achieves an outstanding testing accuracy of 95.45%, as depicted in Figure 5. Analysis of the classification results across four distinct categories reveals that the ADEMNET architecture surpasses the DEMNET model in terms of accuracy, precision, recall, and F1-measure. This underscores the effectiveness of the architecture in facilitating enhanced learning, mitigating Class Imbalance through reduced overfitting, and enhancing feature separation.

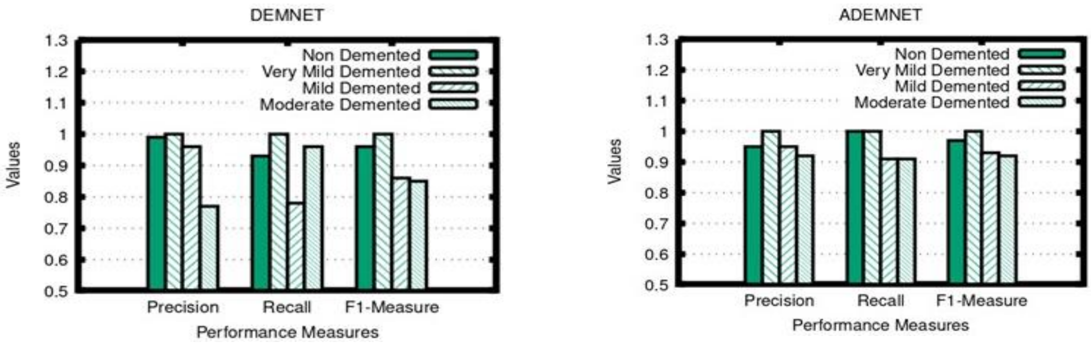

Figure 4. Analyzing average precision, recall, and F1-score for comparative evaluation of specific classes in two architectures

Table 4. Assessment of performance metrics for each class in the ADEMNET architecture

	Precision	Recall	F1-Score
Non-demented	0.95	1.00	0.97
Very mild demented	1.00	1.00	1.00
Mild demented	0.95	0.91	0.93
Moderate demented	0.92	0.91	0.92

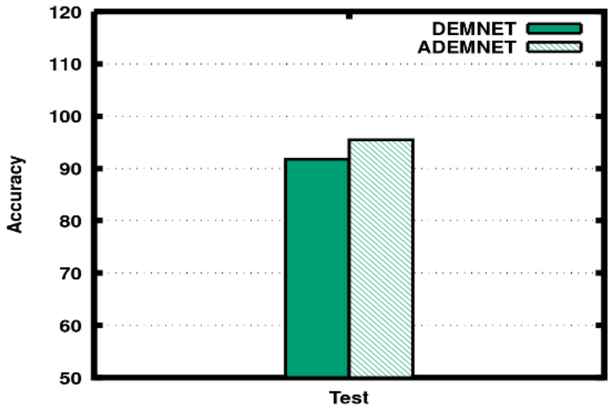

Figure 5. Comparison of test accuracy between DEMNET and ADEMNET architectures

4. CONCLUSION

In conclusion, this research introduces a groundbreaking framework that demonstrates remarkable effectiveness in addressing challenges related to class imbalance. It enables accurate classification of a dementia dataset, encompassing scenarios with four distinct classes. Undoubtedly, the significance of early and precise detection of AD cannot be overstated, as it facilitates timely interventions, efficient management, and improved patient care. Our architectural design integrates advanced methodologies to address the complexities arising from imbalanced data distributions. Remarkably, we achieved an exceptional accuracy rate of 95.45% on the four-class dataset compared with 91.76% for input size 64 * 64. These results emphasize the efficacy of the approach in delivering accurate and reliable predictions across various stages of dementia, showcasing its potential for practical applications. Leveraging artificial intelligence and DL, the goal is to usher in a new era marked by early disease detection, tailored medical interventions, and improved outcomes for patients.

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BIOGRAPHIES OF AUTHORS

Neetha Papanna Umalakshmi is a Research Scholar from the Department of Computer Science and Engineering, University of Visvesvaraya College of Engineering, Bengaluru, India. She completed her Master in Engineering from Computer Science and Engineering, University of Visvesvaraya College of Engineering, Bengaluru, India. Completed her Bachelor's in the same branch from Government Engineering College Hassan, Hassan, India. Currently, she is a Full Time Research Scholar pursing in the specialization “Application of Deep Learning Techniques in Alzheimer's Disease Early Detection”. She received “Best Poster” award in International Conference on Women in Innovation, Technology and Entrepreneurship, IEEE. Her subject interests include AI/ML/DL applications, blockchain benefits, cloud computing, security, and image processing. She can be contacted at email: neethapud@gmail.com.

Simran Sathyanarayana has completed Bachelors of Technology in Computer Science and Engineering from Jain University, Masters of Technology in Computer Networking from University of Visvesvaraya College of Engineering, Bangalore, India. Currently, she is working as a product life cycle management analyst in textron. She can be contacted at email: simrankrithika@gmail.com.

Dr. Pushpa Chicktotlikere Nagappa has completed a Bachelor of Engineering in Computer Science and Engineering from Bangalore University, a Master of Technology from Visvesvaraya Technological University, and Ph.D. in Computer Science and Engineering from Bangalore University. Presently she is working as an Associate Professor in the Department of Computer Science and Engineering at University of Visvesvaraya College of Engineering, Bangalore. She has 23 years of teaching experience. She has presented and published 40+ research papers in reputed International Conferences and refereed International Journals. Currently, she is guiding six Ph.D. students. She received the Outstanding Volunteer-Silver Award from IEEE WIE AG, Bangalore Section, Bangalore in 2019, Best Woman Faculty Award from Novel Research Academy. Puducherry, India, in 2020 and Adarsh Vidya Saraswati Rashtriya Puraskar Best Teacher Award from Global Management Council, India in 2020. Her research interest includes web mining, personalized web search, semantic web and data analytics. She can be contacted at email: pushpacn@gmail.com.

Dr. Thriveni Javarappa has completed a Bachelor of Engineering, Masters of Engineering and Doctoral Degree in Computer Science and Engineering. She has 4 years of industrial experience and 28 years of teaching experience. Currently, she is a Professor in Department of Computer Science and Engineering, University of Visvesvaraya College of Engineering, Bangalore. She has over 120 research papers to her credit. She has produced nine doctorate students and currently guiding eight Ph.D. scholars. Her research interests include computer networks, web mining, IoT, cloud computing and security. She can be contacted at email: drthrivenij@gmail.com.

Dr. Venugopal Kuppanna Rajuk is the Former Vice Chancellor of Bangalore University. He was the Principal of University of Visvesvaraya College of Engineering (UVCE) for 15 years, Chairman, Department of Electronics and Communications, Computer Science Engineering and Information Science Engineering in UVCE. He has a distinguished and brilliant academic career with Eleven degrees including two Ph.D., one in Economics from Bangalore University and another Ph.D. in Computer Science and Engineering from IIT Madras. He has authored and edited 80 books on Computer Science and Economics, which include Petrodollar and the World Economy, C Aptitude, Mastering C, Microprocessor Programming, Mastering C++, and Digital Circuits and Systems. Out of the 101 patents he has filed, 34 have been granted. During his four decades of service at UVCE has over 1000 research papers to his credit and has awarded Ph.D's to 30 students. His research interests include computer networks, wireless sensor networks, parallel and distributed systems, digital signal processing, and data mining. He is a Fellow of IEEE and an ACM Distinguished Educator. This profil can also be found in webpage: https://venugopalkr.com. He can be contacted at email: venugopalkr@gmail.com.