A Unified Deep Learning Framework for Multi-Chronic Disease Classification and Stage Prediction Using Medical Imaging

Mr. V. Anjaiah [1], M. Pallavi[2], CH. Lakshmi[3], J. Vasantha[4], K. Guru Teja[5], K. Srikanth[6]

[1]Assistant Professor, Dept of ECE, PBR VITS, Kavali, Andhra Pradesh, India.
[23456] UG Students Department of Electronics and Communication Engineering,
PBR Visvodaya Institute of Technology & Science, Kavali (Autonomous),
SPSR Nellore (Dt.), Andhra Pradesh – 524201, India.

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ABSTRACT - This paper integrates Internet of Medical Things (IoMT) and deep learning to predict chronic diseases from medical images for early diagnosis in Healthcare 5.0. Traditional methods like Support Vector Machine (SVM) require manual feature extraction and have lower accuracy for complex image data. The proposed system uses DenseNet-201 deep learning model for automatic feature extraction and disease classification. Medical datasets such as pancreatic ultrasound, brain MRI, and Alzheimer's MRI images are used for analysis. The system provides fast, accurate, and automated diagnosis with reduced manual errors, implemented using MATLAB 2020a or above.

1. INTRODUCTION

Recent advancements in digital technologies, especially IoMT and AI, are transforming the healthcare industry by enabling intelligent and connected systems. Moreover, Healthcare 5.0 integrates medical devices, cloud computing, and deep learning to improve diagnosis, monitoring, and treatment. Furthermore, chronic diseases such as brain tumors, Alzheimer's disease, and pancreatic disorders remain major global health challenges. Therefore, early and accurate diagnosis is essential to improve survival rates and reduce healthcare costs. In addition, medical imaging techniques like MRI and ultrasound play a crucial role in detecting these diseases. However, manual analysis by radiologists can be time-consuming and prone to errors. Consequently, deep learning models, particularly CNNs like DenseNet-201, enable automated and accurate image analysis. In this context, the proposed system uses MRI and ultrasound images to classify brain tumors, Alzheimer's stages, and pancreatic disease. Additionally, it incorporates preprocessing, feature extraction, and classification for reliable diagnosis. Overall, the IoMT-enabled framework enhances clinical decision-making, improves efficiency, and supports next-generation healthcare systems.

2. LITERATURE SURVEY

The Centers for Disease Control and Prevention highlights that chronic diseases impose both health and economic burdens, there by emphasizing the need for prevention and early intervention strategies. Moreover, the Center for Managing Chronic Disease explains that chronic conditions require long-term, patient-centered management supported by technology. In addition, CDC fact sheets provide statistical insights, risk factors, and prevention methods, which further justify the urgency of addressing chronic diseases. Furthermore,the study by Agustina Beratarrechea demonstrates that mobile health interventions improve patient adherence, monitoring, and accessibility in healthcare systems. Similarly, Azeem Majeed Hajat and Danielle Stein emphasize the growing challenge of multiple chronic conditions, requiring integrated and technology-driven care approaches. Consequently, these studies collectively highlight the importance of proactive healthcare systems and advanced digital solutions. In this context, research by Haidong Wang and Ali Javanbakht on maternal mortality further underscores global health disparities and the role of data-driven strategies. Overall, these references strongly support the adoption of IoMT-enabled and AI-based frameworks for improving healthcare outcomes and reducing the global burden of chronic diseases.

3. EXISTING METHOD

The existing methodology consists of preprocessing, segmentation, and classification stages, where MR brain images are resized, converted to grayscale, and filtered to remove noise. Subsequently, U-Net-based segmentation is applied to extract important brain regions and eliminate irrelevant background information. After that, the processed images are categorized into four Alzheimer's stages and split into training and validation sets with data augmentation. Finally, DenseNet-201 with transfer learning is used for classification, and the model is evaluated using various performance metrics to ensure accuracy and reliability.

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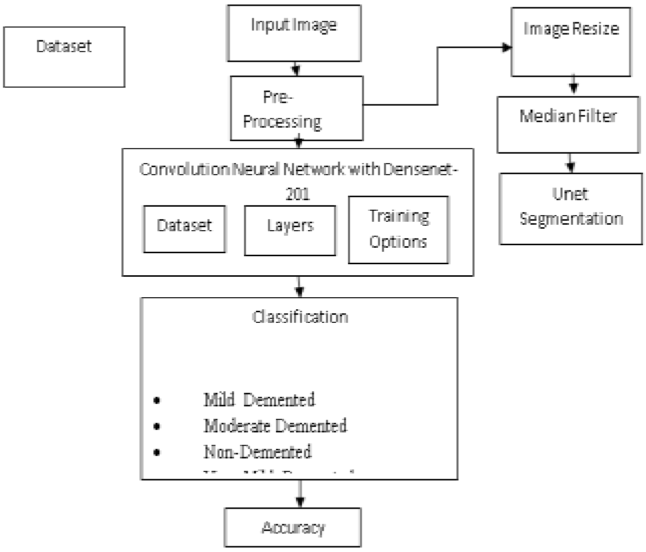


Fig.1: Block Diagram of Existing Method

4. PROPOSED METHOD

The proposed methodology integrates IoMT-enabled Healthcare 5.0 with deep learning for effective chronic disease prediction using medical imaging datasets. Initially, pancreatic ultrasound and brain MRI images are preprocessed through resizing, noise reduction, and contrast enhancement to improve quality. Subsequently, DenseNet-201 is used for feature extraction and classification of brain tumors, pancreatic diseases, and Alzheimer's types. Furthermore, the system performs tumor stage prediction and categorizes diseases into multiple classes using automated pipelines with minimal human intervention. Finally, the model is evaluated using performance metrics like accuracy, precision, and recall, ensuring a reliable and scalable solution for early diagnosis and personalized healthcare.

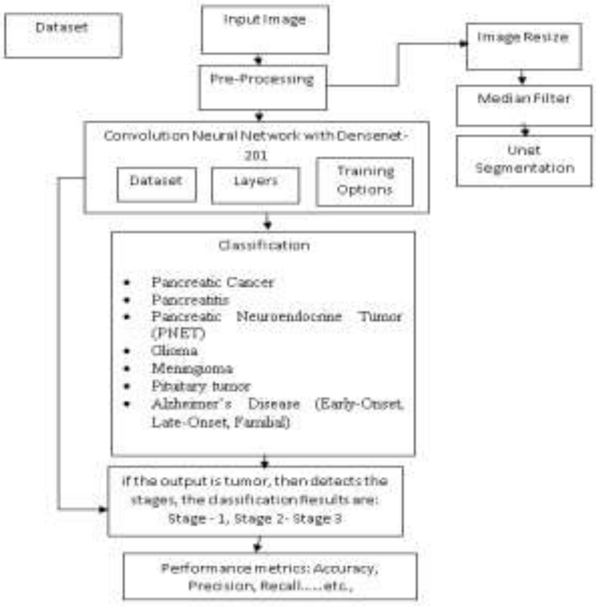


Fig.2: Block Diagram of Proposed Method

In the Fig.3 represents initially, preprocessing techniques such as image resizing, noise removal using median filtering, and contrast enhancement are applied to improve image quality. Subsequently, DenseNet-201, a CNN-based architecture, is utilized for efficient feature extraction and classification of brain tumors, pancreatic diseases, and Alzheimer's types. Furthermore, the system classifies diseases into multiple categories and performs tumor stage prediction using automated pipelines with minimal human intervention. Overall, the framework is evaluated using performance metrics like accuracy, precision, and recall, providing a scalable and reliable solution for early diagnosis and clinical decision support.

5. RESULTS AND DISCUSSION

Fig.3: Input Image

The above Fig 3 represents, the original brain MRI image is taken as input, containing important anatomical details like gray matter, white matter, and ventricles for analysis.

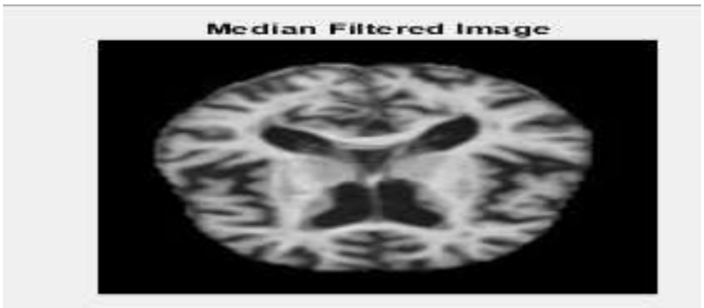


Fig.4: Median Filtered Image

The above Fig.4 represents, the median filtered image is obtained by applying a median filter to remove noise while preserving important edges and structural details.

This process improves image clarity and quality, making it more suitable for further steps like segmentation, feature extraction, and classification.

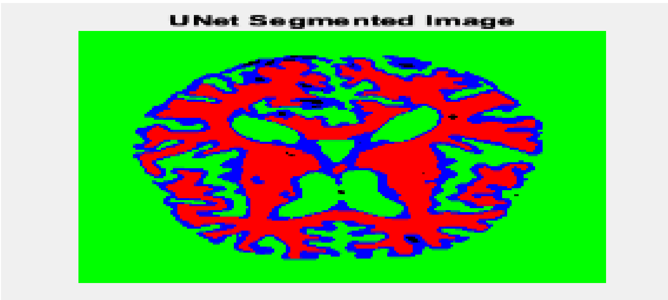


Fig.5: UNet Segmented Image

The above Fig.5 represents, the median filtered image is processed using the U-Net model, which identifies and separates important brain regions from the background for better analysis.

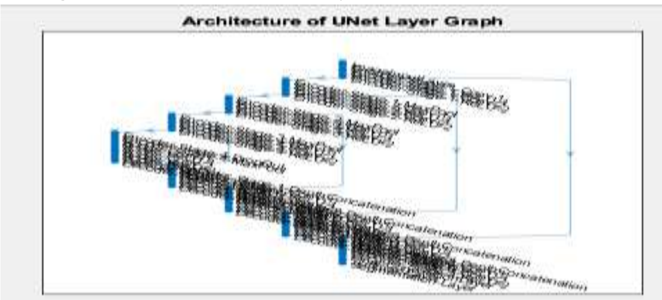
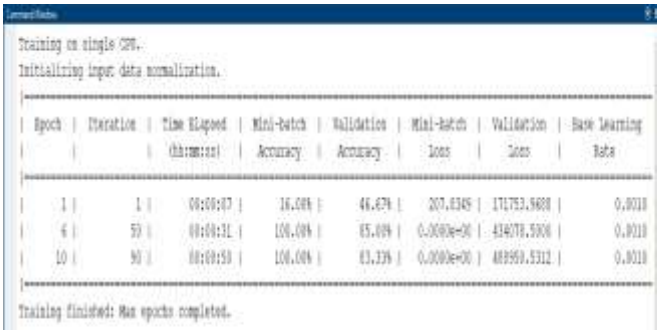


Fig.6: Unet Architecture

The above Fig.6 represents, the U-Net architecture processes preprocessed brain images using an encoder–decoder structure with skip connections to extract features and generate accurate brain region segmentation.

Fig.7: Training Progress Image

The Fig.7 shows how a deep learning model learns from MRI training data, with loss decreasing and accuracy increasing over time. The blue line (training accuracy) indicates how well the model fits the training data, while the orange line (validation accuracy) shows how well it generalizes to new data. The black dotted lines represent validation checks, helping detect proper learning, overfitting, or underfitting during training.



Training on single CPU.
Initializing input data normalization.

Epoch	Iteration	Time Elapsed (hh:mm:ss)	Mini-batch Accuracy	Validation Accuracy	Mini-batch Loss	Validation Loss	Base Learning Rate
1	1	00:00:07	16.04%	46.67%	207.0349	171753.5688	0.0010
6	50	00:00:31	100.00%	65.00%	0.0000e+00	434078.5908	0.0010
10	90	00:00:53	100.00%	83.33%	0.0000e+00	488959.5312	0.0010

Training finished: Max epochs completed.

Fig.8: Training Iterations

The above Fig.8 shows processed training data where the model updates weights in each epoch using backpropagation to reduce error. Epoch means one full pass of the dataset, while iterations are smaller batch updates within each epoch. The graph of iterations vs loss/accuracy helps understand convergence and training stability over time. Metrics like mini-batch/validation accuracy and loss, along with learning rate and time elapsed, evaluate model performance and learning speed.

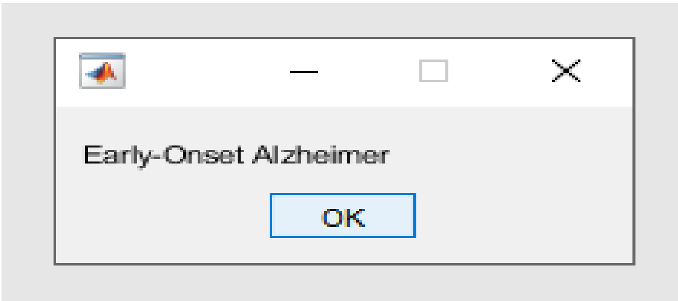


Fig.9: Disease Classification Results

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The Fig.9 represents, the model further classifies the stage of Alzheimer's disease. Stages such as: Mild, Moderate, Severe. The diagram illustrates how a deep learning-based classification system processes medical input data, identifies disease patterns, and presents the final diagnosis "Early-Onset Alzheimer" through a user-friendly interface, enabling accurate and efficient medical analysis. Helps doctors understand disease progression.

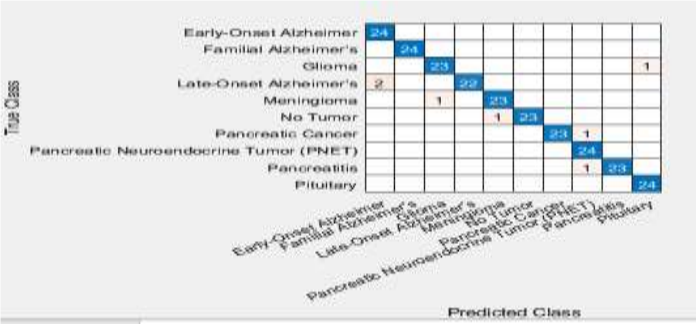

Fig.10: Confusion Matrix

The above Fig.10 shows a confusion matrix that compares actual diseases (rows) with the model's predicted classes(columns).The diagonal values represent correct predictionsThe off-diagonal values represent misclassification. where one disease is incorrectly predicted as another. Small error values (such as 1 or 2) indicate minor confusion, while strong diagonal values show good overall accuracy.

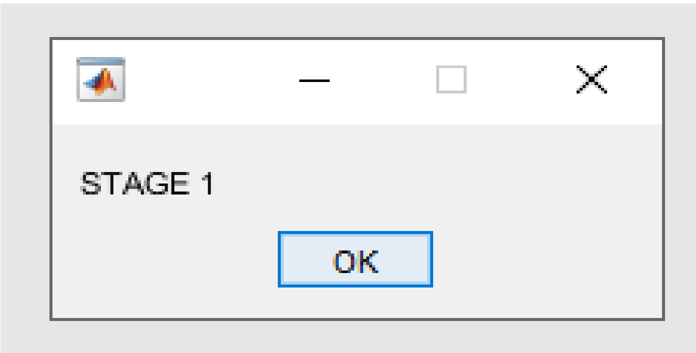

Fig.11: Stage Classification Results

The above Fig.11 shows the stage of the disease. It illustrates how a trained machine learning model processes input data, classifies it into a specific stage, and presents the result through a user-friendly interface, where the prediction "STAGE 1" indicates an early stage detection of the condition.

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Accuracy: 97.08%
Precision: 97.23%
Recall (Sensitivity): 97.08%
F1-score: 97.09%
Specificity: 99.68%
AUC: 98.38%
MSE: 0.3118
PSNR: 5.06 dB
Entropy: 5.4113
Matthews Correlation Coefficient (MCC): 9.5672
Mean Intensity: 0.2505
Standard Deviation: 0.2881
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Fig.12: Metric Values

The above Fig 12 shows the performance Metrice values. By following formulae:

Accuracy = (TP + TN) / Total →Eqn.(1)

Precision = TP / (TP + FP) →Eqn.(2)

Recall = TP / (TP + FN) →Eqn.(3)

F1 = 2 × (Precision × Recall) / (Precision + Recall) →Eqn.(4)

Specificity = TN / (TN + FP) →Eqn.(5)

6. FUTURE SCOPE AND CONCLUSION

The "A Unified" paper has strong future potential in enhancing digital healthcare through advanced AI, IoMT devices, and data analytics. Moreover, it can be expanded with deep learning models and larger datasets to improve early detection of diseases like Alzheimer's, Parkinson's, diabetes, and cardiovascular conditions. Furthermore, the integration of wearable devices, along with cloud and edge computing, will enable real-time monitoring and faster remote healthcare services. In addition, future improvements in mobile applications, data security, and personalization will lead to smarter, safer, and more efficient healthcare systems.

In this paper conclusion, the integration of Internet of Medical Things (IoMT) with deep learning supports Healthcare 5.0 by enabling accurate and early prediction of chronic diseases. The proposed system uses DenseNet-201 with automated image preprocessing, feature extraction, and classification to analyze medical images. It effectively detects Pancreatic Cancer, Brain Tumor, and Alzheimer's disease, and classifies them into different types or stages using ultrasound and MRI datasets. The results show high accuracy and reliability, helping doctors make better decisions, support early diagnosis, and improve personalized patient treatment.

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