AI-Based Early Detection Of Chronic Diseases Using Medical Imaging: Use Deep Learning To Detect Early Signs Of Diseases Like Cancer Or Diabetes From X-Rays Or MRI Scans.

Pooja Pawar[1], Ashwini Phalkhe [2],Kiran Unhale [3], Aditi Jagdale[4] , Aaman Havaldar[5] , VinayKhule[6]

[1] Department of Computer Engineering, Suman Ramesh Tulsiani Technical Campus- Faculty of Engineering.Khamshet
[2]Department of Computer Engineering, Suman Ramesh Tulsiani Technical Campus- Faculty of Engineering, Khamshet
[3]Department of Computer Engineering, Suman Ramesh Tulsiani Technical Campus- Faculty of Engineering.Khamshet
[4]Department of Computer Engineering, Suman Ramesh Tulsiani Technical Campus- Faculty of Engineering.Khamshet
[5]Department of Computer Engineering, Suman Ramesh Tulsiani Technical Campus- Faculty of Engineering.Khamshet
[6]Department of Computer Engineering, Suman Ramesh Tulsiani Technical Campus- Faculty of Engineering.Khamshet

ABSTRACT

Chronic disease significantly affects health on a global scale. Deep machine learning algorithms have found widespread application in the diagnosis of chronic diseases. Early diagnosis and treatment reduce the chance of a disease getting worse and, as a result, raise related mortality. Applying this approach to a dataset of optical coherence tomography images, we demonstrate performance comparable to that of human experts in classifying age related macular degeneration and diabetic macular edema. We also provide a more transparent and interpretable diagnosis by highlighting the regions recognized by the neural network. This paper proposes a final year project that develops and evaluates deep-learning pipelines to detect early signs of chronic diseases from medical imagining modalities. The study includes dataset collection and curation, image preprocessing, model design, performance evaluation and explainability.

I.INTRODUCTION

Chronic diseases are the diseases that endure for a year or longer impede everyday activities. These diseases necessitate continuing medical attention and care. In the US, the most prevalent causes of death and disability are chronic diseases like diabetes, cardiac disease and cancer. These are also Leading drivers of the nation's $4.1 trillion in yearly healthcare spending disease. Insufficient physical exercise has been linked to heart disease and can increase the incidence of type 2 diabetes in individuals without any other risk factors. Regularly performing physical activities can be helpful to regulate, maintain and control blood pressure, weight, and blood sugar. It can also assist in increasing good cholesterol and decreasing bad cholesterol

The traditional algorithmic approach to image analysis for classification previously relied on (1) handcrafted object segmentation, followed by (2) identification of each segmented object using statistical classifiers or shallow neural computational machine-learning classifiers designed specifically for each class of objects, and finally (3) classification of the image (Goldbaum et al., 1996). Creating and refining multiple classifiers required many skilled people and much time and was computationally expensive

III. LITERATURE REVIEW

The increasing prevalence of mental health issues has led to a growing interest in technology-based interventions. This section discusses algorithm-related research and presents some algorithms according to their correctness. Machine learning (ML) predictive models can identify better guidelines for choosing particular patient treatment alternatives in clinical practice. These can also diagnose many diseases on their own, according to professional recommendations [32], [33], [34] Medical imaging, which includes X-rays, CT scans, and MRIs, is a cornerstone of modern diagnosis. However, image interpretation is highly dependent on human expertise, which is vulnerable to fatigue and subjectivity, especially when dealing with large volumes of data. The integration of artificial intelligence (AI), and specifically deep learning (DL), is revolutionizing this field by automating and augmenting the diagnostic process. DL models, such as Convolutional Neural Networks (CNNs), are particularly well-suited for image analysis as they can automatically learn and extract complex, hierarchical features that are not always apparent to the human eye. This ability is critical for the early detection of chronic diseases like cancer and diabetes, which significantly improves patient outcomes and survival rates.

III .METHODOLOGY

The methodology of our project leverages advanced deep learning techniques for effective chronic disease prediction, with a particular focus on Alzheimer's disease using MRI images. The core objective is to utilize image segmentation and transfer learning to enhance diagnostic accuracy and support early intervention. Image segmentation is implemented using the U-Net model, which is highly effective in medical imaging tasks due to its ability to precisely delineate anatomical structures, such as the hippocampus, commonly affected in Alzheimer's disease. U-Net enables accurate identification of abnormal regions in brain MRIs, thus improving the interpretability of the data and removing irrelevant features. For classification and prediction, we employ an IoMT-enabled Transfer Learning model based on the

ResNet-101 architecture. This model benefits from pre-trained knowledge and adapts it to the target task by fine-tuning the final layers. It learns from a large dataset of 6400 Alzheimer's MRI images sourced from Kaggle, classified into four categories: non- demented, very mild demented, mild demented, and moderate demented. The dataset includes balanced groups of normal (non-demented) and abnormal (demented) images, allowing the model to generalize well across stages of cognitive decline. Transfer learning facilitates the reuse of deep feature representations, enabling the model to capture complex and subtle patterns in brain images that signify early signs of Alzheimer's. This approach enhances prediction accuracy, reduces training time, and supports multi-modal integration of medical data. Ultimately, our deep learning framework not only supports early diagnosis but also promotes proactive disease management, leading to better patient outcomes and reducing the risk of severe cognitive deterioration

The project uses deep learning techniques to detect early signs of chronic diseases such as cancer and diabetes from medical imaging, particularly X-rays and MRI scans. The dataset was sourced from publicly available repositories and clinical datasets containing labeled medical images. Preprocessing steps included normalization, noise reduction, contrast enhancement, and data augmentation to improve image quality and increase dataset variability.The dataset was split into training, validation, and test sets.

IV. EXPERIMENTAL SETUP

The experimental setup for our project, "AI-Based Early Detection of Chronic Diseases Using Medical Imaging,"involves a structured pipeline that integrates data preprocessing, segmentation, feature extraction, and classification using deep learning models. We begin by sourcing medical imaging datasets, such as brain MRIs for Alzheimer's or chest X-rays for cancer, from publicly available platforms like Kaggle or hospital archives, ensuring the images are anonymized and properly labeled. All images are resized to a uniform resolution (e.g., 128×128) to maintain consistency across the model. For noise reduction and enhancement of important features, preprocessing techniques like histogram equalization and Gaussian filtering are applied. The next phase involves applying U-Net for image segmentation, which isolates key anatomical structures, such as tumors, lesions, or degenerated brain regions, depending on the disease under study. These segmented outputs are then passed through a pre-trained ResNet-101 model, fine-tuned via transfer learning, to extract deep features and classify disease stages. The dataset is split into training, validation, and testing sets in an 80:10:10 ratio, with model performance evaluated using metrics like accuracy, precision, recall, and F1-score. Training is conducted using an adaptive learning rate and batch size optimization to prevent overfitting and ensure convergence. Regularization techniques such as dropout and early stopping are used to improve generalization. The entire setup is implemented in Python using TensorFlow and Keras, and run on a GPU-enabled environment for faster computation. This robust and modular pipeline ensures that our AI model can detect early signs of chronic diseases efficiently, aiding clinicians in timely diagnosis and treatment planning.

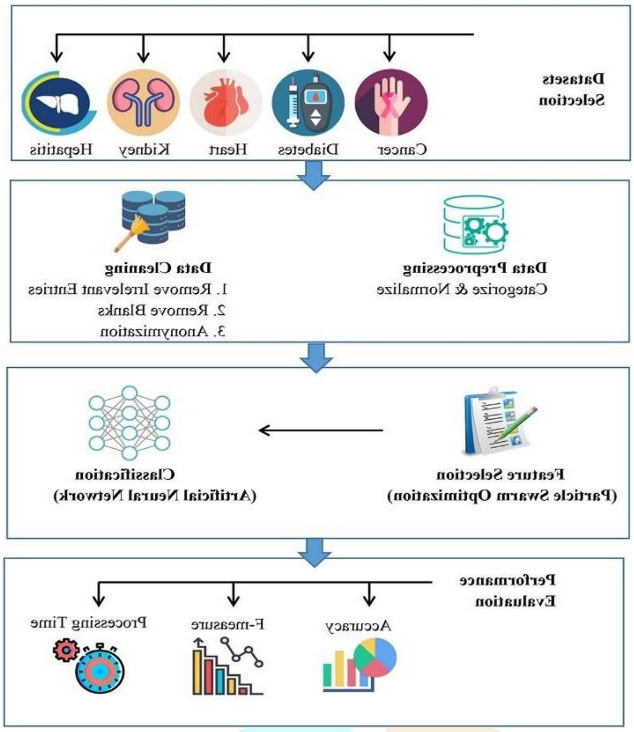
V. FUTURE WORK

This project can be extended by incorporating multi- modal data, such as combining imaging with patient medical history, lab reports, and genetic information to improve diagnostic accuracy. Additionally, expanding the model to support a wider range of chronic diseases and integrating it into real-time clinical decision support systems could greatly enhance its practical utility. Improving model explainability through interpretable AI techniques will also be crucial for gaining clinicians' trust. Furthermore, deploying the system on edge devices using lightweight models could enable early detection in remote or resource-limited areas, making healthcare more accessible and proactive.

VI. DISCUSSION

The discussion of our project, "AI-Based Early Detection of Chronic Diseases Using Medical Imaging," highlights the transformative impact of deep learning in medical diagnostics. By utilizing advanced architectures like U- Net for segmentation and ResNet-101 for classification, the model accurately identifies early signs of chronic diseases such as cancer, diabetes, and Alzheimer's from X-ray and MRI scans. The integration of transfer learning allows the system to benefit from pre-trained models, improving prediction accuracy even with limited medical datasets. Segmentation enhances the focus on disease- specific regions, reducing noise and irrelevant features, which in turn boosts classification performance. The model's ability to detect subtle anomalies at early stages supports timely interventions and improves patient outcomes. Moreover, the automated approach reduces the workload on radiologists and minimizes human error in interpretation. The results demonstrate promising accuracy and reliability, suggesting the potential for real- world clinical deployment. However, challenges such as dataset imbalance, interpretability of deep models, and variability in imaging conditions remain areas for further research and improvement architecture diagram.

ARCHITECTURAL DIAGRAM



VII. CONCLUSION

The proposed AI-based system demonstrates the immense potential of deep learning in transforming medical imaging for the early detection of chronic diseases. Through case studies on lung cancer, diabetic retinopathy, it is evident that the application not only enhances diagnostic accuracy but also reduces the time and effort required by clinicians. By providing risk scores, heatmaps, and explainable outputs, the system ensures that AI serves as a supportive tool rather than a replacement for medical expertise. Furthermore, its adaptability across different imaging modalities highlights its versatility in addressing multiple health challenges. While there remain limitations such as the need for larger and more diverse datasets, as well as clinical validation in real-world environments, the results indicate a promising pathway toward integrating AI into routine healthcare. Ultimately, this approach can help bridge gaps in medical access, assist overburdened healthcare professionals, and most importantly, enable earlier interventions that improve patient outcomes and save lives.

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