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Automated Approach to detect Brain Disease Anomalies

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ABSTRACT:

The brain is the body's central nervous system. As time goes on, more and more brain disorders are being identified. Thus, current technologies for diagnosis or detection are getting more difficult to utilise and remain an unsolved research problem due to the variety of brain illnesses. Early brain disease detection can be extremely beneficial in the fight for a cure. Artificial intelligence (AI) has become increasingly prevalent in all fields of science in recent years, and neurology is undoubtedly being revolutionised by it. This paper reviews the state-of-the-art methods for identifying four brain disorders, including epilepsy, Parkinson's disease, brain tumours, and Alzheimer's disease (AD). The most often utilised datasets as the main source of brain disease data in the reviewed publications are discussed, totaling twenty-two. In conclusion, a summary of the most important discoveries from the examined papers is provided, along with a discussion of many significant problems concerning deep learning/machine learning approaches for diagnosing brain diseases. With this research, we hope to identify the most reliable method for distinguishing between various brain disorders, which will be useful in the future.

I. INTRODUCTION

The human body is composed of numerous types of cells. Each cell has specific function. These cells in the body grow and divide in an arranged manner and form some new cells. These new cells help to keep the human body healthy and ensures proper functioning. The conventional method for brain detection in magnetic resonance brain images in human inspection. The observation from human in predicting the disease may mislead due to noise and distortions found in the images. So, automated brain detection methods are developed as it would save radiologist time. The MRI brain detection task due to complexity and variant of diseases. Pre-processing steps are applied on the brain MRI images, then texture features are extracted using Gray Level Co-occurrence Matrix (GLCM) and finally classification is performed using machine learning algorithm. In the medical field, Brain disease is detected by Doctors by referring the images of MRI images which is very time consuming. Therefore, to overcome this problem , an alternative way is to design the system that will automatically identify the presence of disease in MRI images using machine learning technique and also provide faster and accurate solutions.

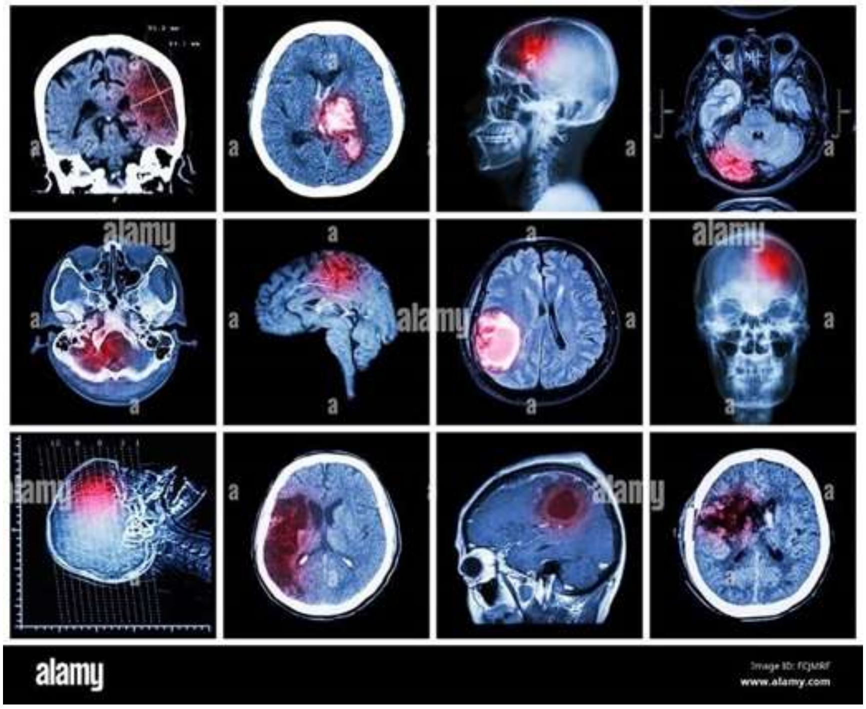

Fig. 1. Basic image of brain

II. LITERATURE REVIEW

The literature on detecting brain diseases encompasses a broad spectrum of research, reflecting the interdisciplinary nature of this critical healthcare domain. Numerous studies delve into the utilization of advanced imaging techniques, such as magnetic resonance imaging (MRI) and computed tomography (CT), to identify structural abnormalities indicative of various neurological disorders. Machine learning algorithms have emerged as pivotal tools, showcasing applications in image analysis, classification, and predictive modeling. Researchers have explored diverse approaches, from traditional image processing methods to sophisticated deep learning architectures, seeking to enhance the accuracy and efficiency of brain disease detection. Integration with electronic health records (EHR), ethical considerations in handling sensitive medical data, and collaborative efforts between medical experts and data scientists are recurring themes in the literature

Additionally, studies often emphasize the need for interpretability, transparency, and real-world clinical relevance in developing robust brain disease detection systems. As the field evolves, this literature review underscores the importance of continuous advancements, interdisciplinary collaboration, and ethical frameworks to address the challenges and opportunities in the detecting of brain diseases.

III. METHODS AND MATERIAL

Detecting brain diseases involves a combination of advanced methods and materials, including medical imaging technologies, computational techniques, and data sources. Here's an overview:

1. Imaging Modalities:

- Magnetic Resonance Imaging (MRI): Provides detailed structural images of the brain, crucial for identifying abnormalities like tumors, lesions, and atrophy.

- Computed Tomography (CT): Produces cross- sectional images, useful for detecting hemorrhages, fractures, and structural changes..

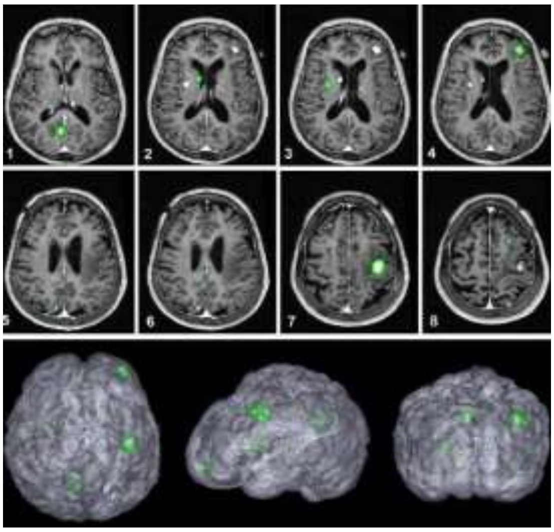

Fig. 2.1. Image modularity of brain

2. Feature Extraction:

- Texture Analysis: Quantify spatial patterns and textures within images.

- Shape Descriptors: Capture geometric features of segmented regions.

- Intensity Histograms: Summarize pixel intensities within specific regions

3. Continuous Monitoring and Improvement:

- Feedback Loops: Incorporate feedback from healthcare professionals to refine and improve the model.

- Adaptability: Update models to accommodate new data and evolving medical knowledge.

4. Image Segmentation:

- Tumor Segmentation: Identify and delineate tumor boundaries within brain images.

- Brain Region Segmentation: Divide the brain into distinct regions for detailed analysis.

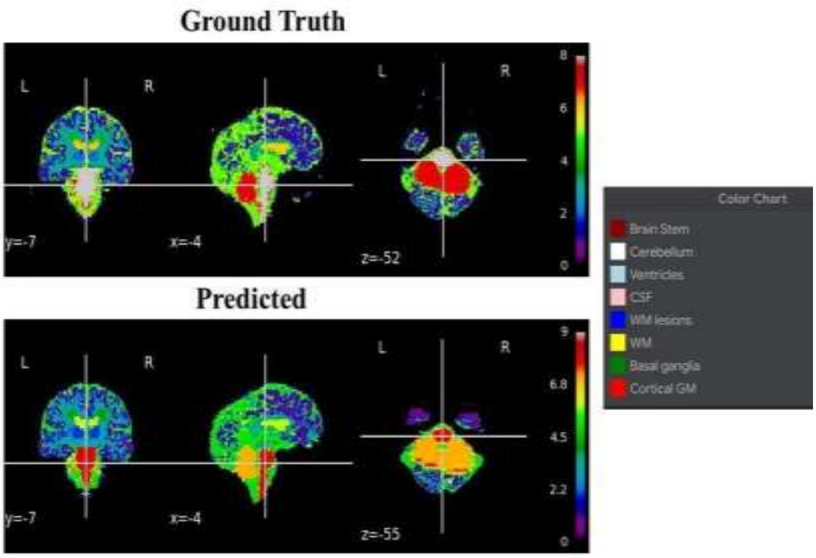

Fig: 2.2. Brain Segmentation

5. Validation and Testing:

- Cross-Validation: Assess model performance across different data splits.

- Metrics: Use accuracy, precision, recall, F1 score, and area under the receiver operating characteristic (ROC) curve to evaluate model effectiveness.

6. Machine Learning Algorithms:

- Convolutional Neural Networks (CNNs): Effective for image-based tasks, particularly useful in extracting hierarchical features.
- Ensemble Methods: Combine predictions from multiple models for improved performance.

7. Interpretability and Visualization:

- Explainability: Ensure that the model's decisions are interpretable, especially in a clinical setting.
- Visualization Tools: Provide clinicians with tools to interpret and interact with model outputs.

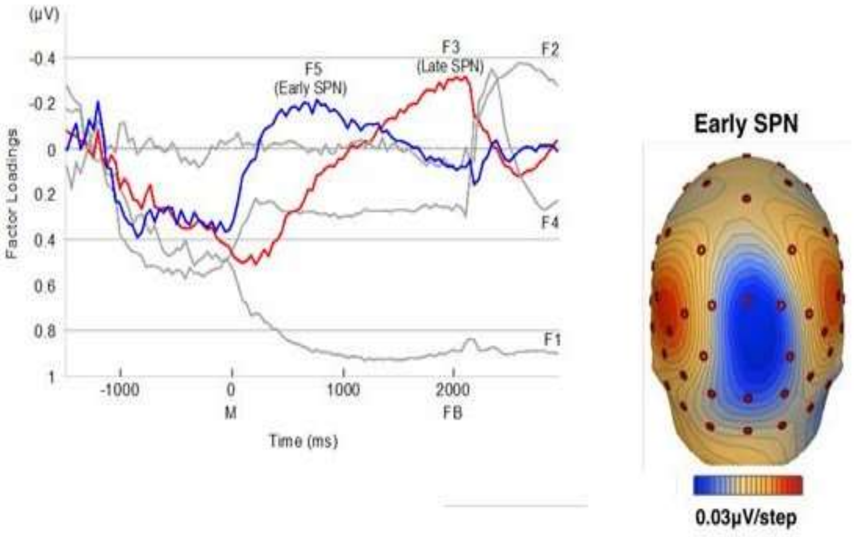

Fig : 2.3. Brain Visualization

IV. RESULTS AND DISCUSSION

The field of brain disease detection has witnessed remarkable progress through the integration of cutting- edge technologies, computational methodologies, and medical expertise. The utilization of advanced imaging modalities, such as MRI and CT scans, has significantly enhanced our ability to visualize and identify subtle abnormalities in the brain. The marriage of these imaging techniques with sophisticated machine learning algorithms, ranging from traditional methods to deep learning architectures, has paved the way for accurate and early detection of various neurological conditions.

Looking forward, future enhancements in brain disease detection are likely to be fueled by ongoing technological advancements, including higher-resolution imaging, more sophisticated machine learning algorithms, and the integration of real-time monitoring technologies. As this field evolves, the collaborative efforts of professionals from diverse disciplines will play a central role in shaping the future landscape of brain disease detection, ultimately contributing to improved diagnostics and personalized treatment strategies for individuals facing neurological challenges.

Using Logistic Regression:

```
array([[ 0.20973597, -1.05364663,  0.12282256, ..., -0.54411384,
        -0.91364312, -1.23917737],
       [ 0.41407657,  0.46413913,  0.47638457, ...,  1.54690555,
         0.15432144,  1.15144623],
       [-0.19598379,  0.58308786, -0.24103737, ..., -0.04967407,
         0.13995421, -0.68588412],
       ...,
       [-0.71423895,  1.26347458, -0.66196495, ...,  0.25651928,
        -0.16495047,  0.8703909 ],
       [ 1.51277751, -0.13298348,  1.44610561, ...,  1.47973048,
         1.00677746, -0.05323408],
       [-1.3314068 , -0.54454608, -1.29399994, ..., -0.51833736,
         0.12079789,  0.79048301]])
```

Fig .4.1. L.R.Model

Using Decision Tree :

```
array([0, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1,
       1, 0, 1, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0,
       1, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0,
       0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 0, 1, 1, 1, 0, 1, 1, 1, 0, 1, 0,
       1, 1, 1, 1, 0, 1, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0,
       0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 1,
       1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0], dtype=int64)
```

Fig .4.2. D. T. Model

Using Random Forest :

```
array([0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1,
       1, 0, 1, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0,
       1, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0,
       0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 1, 0, 1, 0,
       0, 1, 1, 1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0,
       0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 1,
       1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0], dtype=int64)
```

Fig 4.3. R.F. Model

Using Support vector machine:

```
array([0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1,
       1, 0, 1, 1, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0,
       1, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0,
       0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 1, 0, 1, 0,
       0, 0, 1, 1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0,
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       1, 0, 0, 1, 0, 0, 1, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0], dtype=int64)
```

Fig 4.4. SVM Model

V. ARCHITECHTURE

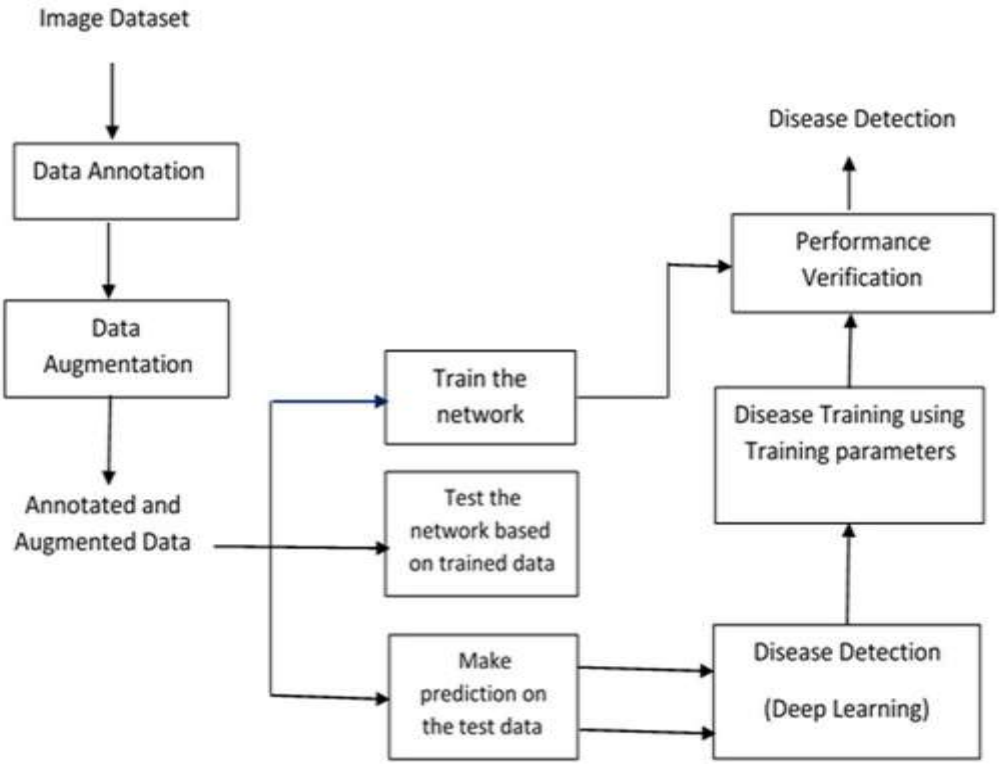

Fig 5. Architecture

VI. CONCLUSION

In conclusion, the realm of brain disease detection stands at the intersection of medical innovation and technological advancement, holding great promise for the future of neurological healthcare. The integration of state-of-the-art imaging modalities, computational methodologies, and machine learning algorithms has ushered in a new era of early and accurate diagnosis. The significance of curated datasets, ethical considerations, and interdisciplinary collaboration has been pivotal in the development of robust and reliable detection systems. These innovations aim to enhance early detection, improve accuracy in diagnosis, and provide a more proactive approach to managing and understanding brain health. Continued research and interdisciplinary collaborations will play a crucial role in realizing these advancements and addressing the complexities of detecting various brain diseases.

VII. FUTURE ENHANCEMENT

The future of detecting brain diseases may involve advancements in non-invasive imaging technologies, such as improved functional MRI (fMRI) or more sensitive brain scans. Integration of artificial intelligence in analyzing complex neural patterns could enhance early detection and diagnosis. Additionally, innovations in wearable devices and biosensors might enable continuous monitoring of brain health, offering a proactive approach to identifying abnormalities. Ongoing research in neurobiology and machine learning could pave the way for more accurate and personalized diagnostic tools.

Furthermore, the development of biomarkers, either through neuroimaging or molecular analysis, may enable more precise and early detection of specific brain disorders. This could lead to personalized medicine approaches tailored to individual patients based on their unique neurobiological profiles.

Additionally, the ongoing exploration of novel technologies, such as neurophotonics or advanced brain- computer interfaces, may contribute to breakthroughs in understanding and diagnosing brain diseases. The combination of technological innovation and a deeper understanding of the brain's complexities holds the key to more effective and early detection of various neurological conditions.

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