Using Generative Adversarial Networks and Ensemble Learning for Multi-Modal Medical Image Fusion to Improve the Diagnosis of Rare Neurological Disorders

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***Abstract*—The research suggests a unique ensemble learning approach for precise feature extraction and feature fusion from multi-modal medical pictures, which may be applied to the diagnosis of uncommon neurological illnesses. The proposed method makes use of the combined characteristics of Convolutional Neural Networks and Generative Adversarial Networks (CNN-GAN) to improve diagnostic accuracy and enable early identification. In order to do this, a diverse dataset of multi-modal patient medical records with rare neurological disorders was gathered. The multi-modal pictures are successfully combined using a GAN-based image-to-image translation technique to produce fake images that effectively gather crucial clinical data from different paradigms. To extract features from extensive clinical imaging databases, the research employs trained models using transfer learning approaches with CNN frameworks designed specifically for analyzing medical images. By compiling unique traits from each modality, a thorough grasp of the core pathophysiology is produced. By combining the strengths of several CNN algorithms using ensemble learning techniques including voting by majority, weight averaging, and layering, the forecasts were also integrated to arrive at the final diagnosis. In addition, the ensemble approach enhances the robustness and reliability of the assessment algorithm, resulting in increased effectiveness in identifying unusual neurological conditions. The analysis of the collected data shows that the proposed technique outperforms single-modal designs, demonstrating the importance of multi-modal fusion of pictures and feature extraction. The proposed method significantly outperforms existing methods, achieving an accuracy of 99.99%, as opposed to 85.69% for XGBoost and 96.12% for LSTM. The proposed method significantly outperforms existing methods, achieving an average increase in accuracy of approximately 13.3%. The proposed method was implemented using Python software.**

Keywords*—Multi-modal medical images; ensemble learning; CNN; GAN; neurological disorders; image-to-image method; transfer learning; feature extraction

I. Introduction

A neurological condition called Alzheimer's disease (AD) causes diminished cognitive abilities as well as memory and mobility problems. As civilization gets older, this illness affects a growing number of elderly people. According to research, poorer nations have a significantly greater incidence of AD than advanced economies do [1]. MCI gradually develops into AD as the disorder progresses, and early mild cognitive impairment (EMCI) and late mild cognitive impairment (LMCI) are transitional states among healthy normal persons and those with Alzheimer's. Therefore, it is crucial to understand the best way to properly diagnose MCI and AD. The prevalence of brain illnesses has increased recently all across the world. One of the world's most prevalent neurological conditions is Alzheimer's disease (AD) that primarily manifests clinically as diminished memory and loss of mental abilities, along with difficulties with language and abnormalities of movement. AD is currently the fifth most common cause fatalities in the United States. The Alzheimer's Disease Association of USA published an article in 2018. The information provided by the Center for Health Statistics on the rate of change in death from a variety of hazardous illnesses in the US [2]. The number of fatalities from various risk conditions has increased. Moreover, 123% rise in AD prevalence has been reported. Another study found that in 2050, there will be around one million new instances of dementia caused by Alzheimer's, with a fresh case being identified every 33 seconds. One of the main illnesses endangering the well-being of elderly people and having an impact on social sustainability is AD. Presently, only a few medications have proven effective for the medical management of AD, and no medication has been proven shown to slow or stop the progression of the disease.

Brain tumors currently have the highest early cost per the patient among malignancies. Tumors can develop in humans of any age due to the enormous cell growth in some areas of the cerebral cortex. Brain lesions are caused by uncontrolled growth of cerebral or central spine tissue that can impair cognitive function [3]. These enormous cells of tumors can be divided into two distinct groups: malignant and non-malignant lymphocytes depending on the region, magnitude, and location. The primary and subsequent tumor sites are the intense regions of cancerous cells. The initial tumor region is defined as the first, harmless stages of cancerous cells. According to similar research, numerous medical CBIR approaches have recently been introduced. Most advanced CBIR recovery techniques utilize just one kind of illumination [4]. One method to find the necessary healthcare images over huge collections of images is to employ resemblance contrast, and extraction techniques can allow the user to select the image category first. A CBIR algorithm may gain a lot from effective picture classification because it could eliminate the need to look over pointless images, cutting down on the total amount of images the software must look through.

Non-invasive cerebral imaging techniques have become popular in the past few decades for diagnosing AD. According to these benefits, this method of imaging is both extremely efficient and benign to human cerebral regions [5]. With regard to these benefits, doctors frequently select non-invasive clinical imaging of the brain as one of the most significant medical assessment tools. The images from multiple modes can emphasize various topographical features and geographical aspects of the brain due to the various image philosophies and techniques. Researchers are able to categorize and recognize sufferers more accurately via acquiring these traits, enabling early identification and treatment of diseases. Although modern deep learning techniques are efficient in assessing clinical images of disease progression in AD. In earlier times, scientists have employed spectral evaluation and time-frequency distribution methods like the discrete wavelet transformation method (DWT) and the Fourier transformation method (FT). It is difficult to establish a generic approach for studying different feelings, nevertheless, considering how complicated and personal the mental state is. Frequency component knowledge is insufficient for classifying human feelings for non-stationary EEG signals since it changes over time [6]. Consequently, a continuous wavelet transform (CWT) is yet another method utilized to obtain the complete understanding of frequency of signals in the temporal and spatial arena.

Nowadays, numerous neuroimaging techniques offer different kinds of data. A single method may not always yield enough data to pinpoint the distinguishing characteristic needed to locate AD in a patient. This makes it challenging for therapists to detect AD in its infancy by looking solely at the evidence from a single therapy [7]. Brain structural inequality, neurochemical, and behavioral investigations have investigated and studied a number of biomarkers and provided a variety of information. To enhance the diagnostic efficiency of a computer-aided diagnosis (CAD) framework, it is crucial to incorporate the complementing elements from several modalities. Medical image fusion integrates multiple images collected with different methods to improve the image's quality while maintaining the minute details of a single image. The method of fusion enhances visual data and simplicity, which aids in the diagnosis and evaluation of the condition by physicians [8]. Due to the rapid advancement of high-tech and modern devices, diagnostic imaging has become an integral component of a vast array of applications, including evaluation, investigation, and treatment.

Data that covers multiple kinds and situations is referred to as multimodal information. The main goal of techniques employed for combining multimodal information is to combine the data with characteristics of various dimensions and dispersion into a worldwide space of features so that the information can be expressed more accurately [9]. When performing tasks like categorization and estimation, this homogeneity can be utilized. For instance, data from significant bio banks like the UK Biobank, the Million Veterans Program, and the National Institutes of Health All of Us effort include specific to patient’s genome data, diagnostic investigations, and behavioral information from electronic medical records and surveys. Consequently, it is crucial to effectively mix all of the fusion procedures [10]. With minimal computing difficulty, an effective multi-modal fusion technique ought to maximize collaboration among different modes. The Siamese networks have demonstrated outstanding efficiency in a variety of programs, including facial and recognition of handwriting. Furthermore, people transitioning to Alzheimer's disease are identified utilizing an array of recurrent neural network. Although their method is intriguing, it lacks a joint education component that does not calculate ROI-based statistics, which can be inaccurate and cause detection mistakes. To overcome these issues the research produces an ensemble learning approach for multi-modal medical image fusion and feature extraction using convolutional neural networks and generative adversarial networks in diagnosing rare neurological disorders.

The key contributions of the research are given as follows:

- The goal of data collection is to gather multi-modal diagnostic information for neurological illnesses using an ensemble learning approach built on the CNN-GAN technique.
- In order to assure data quality, a thorough data cleaning procedure is used to remove artifacts, noise, and superfluous data.
- The proposed research employs Convolutional Neural Networks, which are recognized for their capacity to automatically collect pertinent organizational traits, are used for feature extraction.
- This work utilizes Generative Adversarial Networks (GAN), which trains on a wider variety of samples to prevent overfitting, are used for data augmentation and picture fusion. In this framework, the discriminator separates created fused pictures from actual images, while the generator aims to create better fused images

that can trick the discriminator and promote adversarial learning.

- When diagnosing unusual neurological illnesses, ensemble learning is used to train several classification models utilizing chosen features, improving accuracy, dependability, and generality.
- To further improve diagnostic accuracy, particularly for illnesses with a low prevalence, ensemble learning incorporates anticipated results from many simulations.

The remaining sections of the research are given as follows. Literature Review is given in Section II. Problem Statement is discussed in Section III. Then Section IV that discusses about the proposed method for diagnosing neurological disorders. Results and Discussions are discussed in Section V. Conclusion is discussed in Section VI.

II. Related Works

Khan et al. [11] discussed in the paper that the body's center of control is the cerebral cortex. As years goes on, more and more brand-new brain disorders have been identified. As a result of the variety of neurological conditions, current diagnosing or detection methods are growing difficult and remain an unsolved scientific issue. Early diagnosis of brain disorders can have a significant impact on efforts to treat them. Artificial intelligence (AI) has been increasingly prevalent in the past few decades, altering virtually every aspect of research, including neuroscience. The deployment of AI in clinical studies has improved the accuracy and precision of neurological conditions diagnosis and treatment. In this research, researchers evaluate current advances in machine learning and deep learning for the detection of four distinct brain disorders, including Parkinson's illness, seizures, brain tumors, and Alzheimer's disease.

Brain disorders are mostly brought on by aberrant brain cell proliferation, which can harm the neural network of the central nervous system and finally result in aggressive cancer of the brain said by Musallam, Sherif, and Hussein [12]. Significant challenges exist when utilizing a Computer-Aided Diagnosis (CAD) technology to make an accurate diagnosis that would allow for effective medication, particularly when it comes to accurately identifying various illnesses in magnetic resonance imaging (MRI) images. In this research, a novel Deep Convolutional Neural Network (DCNN) design for effective identification of tumors such as meningioma, and pituitary tumors is put forward with a three-step pre-processing method to improve the presentation of MRI images. For quick instruction with a greater rate of comprehension and simple startup of the component measurements, the structure leverages sequential normalization. The method of detecting brain deviations, which is crucial for determining the extent to which they are present in MRI scans, is regarded as the biggest downside.

Hashem et al. [13] exposed in the paper that in terms of anatomy, the palate and face house 30–40% of the human body's motor and sensory neurons, showing the intimate link between the cavity in the mouth and the nervous system in general. The duties of an oral surgeon are directly related to the detection of orofacial symptoms of neurological conditions. In order to effectively recognize, diagnose, and make the right choices while managing these related neurologic disorders, dental practitioners must become acquainted with these specific presentations. These symptoms should be thoroughly evaluated with cutting-edge methodologies because it's crucial to spot any associated neurological conditions before they have major repercussions. Additionally, much-planned and successful innovative techniques are required for all types of rehabilitation therapies as well as dental treatment for individuals with neurological conditions.

A comparatively recent innovation called the Internet of Medical Things (IoMT) enables the transmission of health information across a safe network of wearables and healthcare sensors. The disadvantage of this research is that IoMT for dental care concentrates mostly on proactive maintenance methods by identifying the root of tooth decay at the earliest opportunity and disseminating information with the oral surgeon and the consumer round-the-clock. The precise identification of Alzheimer's disease (AD) has been made possible by the integration of multi-modal data, such as magnetic resonance imaging (MRI) and positron emission tomography (PET), which both provide complimentary functional and structural data said by Ning et al. [14]. While their fundamental connections might offer additional distinguishing traits for AD detection, the majority of the present approaches merely combine multi-modal characteristics in the initial location. The issue of the overfitting problem brought on by highly dimensional multimodal information that continues to be intriguing. In order to do this, researchers suggest a relation-induced multidimensional shared representational method of learning for identifying AD. The suggested approach combines reduction of dimension, classification simulation, and representational training into a single architecture.

Rathore et al. [15] discussed in the paper that classifying various patterns of attack for profound implants in the brain is the goal of the deep learning approach. The restricted accessibility of labelled information and the substantial patient-to-patient variation in cerebral implantation impulses pose challenges, though. It is crucial to guarantee the model's accuracy and comprehension for healthcare providers and patients as well as its durability over prospective hostile assaults. In order to allow efficient operation on cerebral implantation gadgets, immediate processing and hardware constraints have to be conquered. Issues over patients' privacy and confidentiality, as well as security concerns, must be carefully taken into account. In order to provide an efficient and safe deep learning system for categorizing assault behaviors in profound cerebral devices, it is going to be essential to overcome these challenges.

Around one percent of the global population suffers from epilepsy, a persistent neurological illness that is defined by an increased frequency of uncontrolled convulsions. The majority of the present epilepsy detection techniques depend heavily on historical patient information, which makes them ineffective when trying to identify fresh patients in a patient-independent environment Zhang et al. [16]. To get across this issue, researchers offer a successful framework for detecting seizures caused by epilepsy that improves from epileptic events while reducing inter-patient interference. To identify the original seizure-specific information from the unprocessed non-invasive electroencephalography (EEG) recordings via adversarial learning, a sophisticated deep neural network framework is suggested.

The research examines the significance of accurate diagnosis and early treatment of a variety of brain illnesses and emphasizes the contribution of AI and deep learning to increasing diagnostic precision. Brain tumor identification or facial signs of neurological diseases, IoT in dental care, deep learning for brain implant security, and enhanced epilepsy diagnosis are some of the subjects discussed. The study on utilizing technology to improve our comprehension and treatment of neurological diseases is expanding, and these studies add to that body of knowledge.

III. Problem Statement

From the above discussion the literature reveals that the Siamese networks have demonstrated outstanding efficiency in a variety of programs, including facial recognition [17]. The current approach of detecting uncommon neurological illnesses is promising, but it has flaws in terms of accuracy and robustness, largely because it lacks a collaborative education component that includes trustworthy indicators other than ROI-based data. ROI-based data may be inaccurate and might result in missed diagnoses of neurological illnesses that are infrequent. This research suggests an ensemble learning strategy that incorporates multi-modal medical picture fusion and feature extraction approaches to solve these problems and improve the accuracy and reliability of diagnosis. This method uses generative adversarial networks (GANs) and convolutional neural networks (CNNs) to offer a more thorough and efficient diagnosis for uncommon neurological illnesses.

IV. Proposed Methodology

The approach employed for the research concentrates on creating an innovative technique to identify rare neurological disorders by utilizing the combined strength of Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) for multi-modal medical imaging. The Harvard Atlas Brain dataset is utilized for the process of testing and training. This dataset contains the modality of MRI brain images. This is secondhand to validate the efficiency of the investigation and to diagnose rare neurological disorders. Then, the gathered data are cleaned and any undesirable artifacts, noise, or unimportant data are removed by employing preprocessing procedure. Then, the ensemble learning based on CNN-GAN is utilized for the process of diagnosing neurological disorder. Moreover, it is hired in demand to upsurge accuracy. The recommended CNN-GAN outline's architectural illustration is publicized in Fig. 1.

A. Data Collection

The process of collecting knowledge, data or evaluations from multiple sources to use in investigation, evaluation, decision-making or any other type of specified objective is known as data collection [18]. The Harvard Atlas Brain dataset is utilized for the process of testing and training. This dataset contains the modality of MRI brain images. This is secondhand to validate the efficiency of the investigation and to diagnose rare neurological disorders.

B. Pre-processing

In data analysis and machine learning, pre-processing is a critical phase where unprocessed data is cleaned, converted and structured to render it appropriate for future analysis or model training [19]. Preprocessing aims to enhance the integrity of the data eliminate noise and discrepancies and guarantee that the information arrives in a manner that can be utilized successfully for its intended purpose.

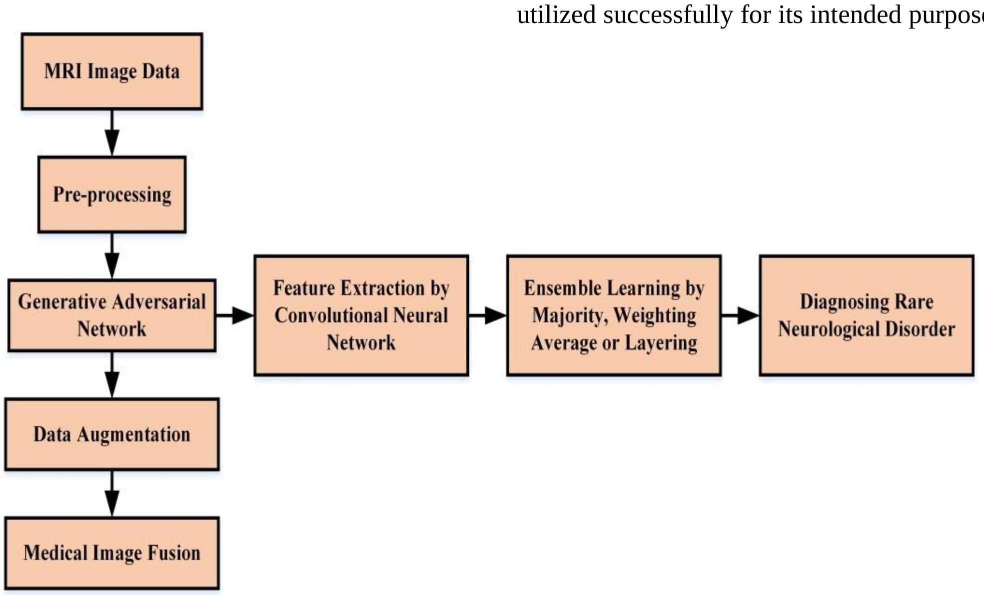

Fig. 1. Proposed ensemble learning based CNN-GAN method.

C. Generative Adversarial Network (GAN)

A machine learning model called a generative adversarial network (GAN) consists of two distinct neural networks such as a discriminator and a generator. Although the system for discrimination attempts to separate genuine data from produced data, the generator creates samples of artificial data. The generator seeks to provide convincing samples to deceive the discriminator, and the discriminator attempts to increase its capacity to distinguish between actual and false information. They are trained in an adversarial manner. GANs can produce high-quality and different information samples via this competitive approach, which makes them valuable for projects like image synthesizing, data enhancement, and style transfer. In Fig. 2, the diagrammatic representation of GAN is depicted.

GANs are employed in multi-modal fusion for the diagnosis of neurological disorders for the reason they are efficient at capturing complicated trends and variations from diverse sources of data, integrating information from multiple sources, performing data enhancement, enabling transfer learning, and aiding in the creation of accurate images or depictions of neurological conditions. By utilizing these skills, GANs improve illness diagnosis' precision, durability, and generalization. The equation for generator and discriminator is given in Eq. (1) below.

$$min_G \, max_D * L(D,G) = F_x \sim P_{data}(x)\left[log\left(D(x)\right)\right] + F_y \sim P_y(y)[log(1 - D(G(y)))] \quad (1)$$

Here, y is represented as the input of the image; D is the denoted as the Discriminator; G is represented as the generator; F is denoted the expectation operator; x is represented as the real samples. This research's efficacy is considerably increased by including generative adversarial networks by tackling major difficulties in identifying uncommon neurological illnesses. When working with little or unbalanced datasets, as is frequently the case with uncommon conditions, GANs excel at producing synthetic data that closely resembles actual medical pictures. In order to ensure a more varied and representative set of medical pictures for training, GANs can help supplement the dataset, which will ultimately result in a more robust model.

1) Data augmentation by GAN: It is a collection of methods for changing duplicates of already-existing data or creating fresh copies of the database intentionally utilizing the data already present [20]. It serves as normalization during machine learning model training and lessens over fitting.

2) Medical image fusion using GAN: Various medical images possess certain distinctive qualities that call for concurrent observation for clinical diagnosis [21]. Therefore, multi-modality image fusion is used to merge the characteristics of several image detectors into a single image. A cutting-edge method called medical image fusion utilizes GAN to combine data from many healthcare imaging techniques into a single, improved representation. The GAN develops to produce combined images that capture crucial elements from each modality by being trained on pairs of medical images from multiple sources. To provide realistic results with an adversarial loss and to protect important anatomical components with a content loss, this technique improves a loss function. The created composite image can be very helpful in enhancing medical analysis, helping to diagnose diseases, organize treatments, and track patients. Utilizing GANs for medical image fusion has the ability to deliver more and thorough educational data, thereby enabling medical practitioners to make better choices for the welfare of their patients. Before implementing an AI-driven strategy into the healthcare sector a thorough validation and compliance to legal requirements are essential.

D. Feature Extraction by Convolutional Neural Network (CNN)

A key step in deep learning for pattern and image recognition applications is feature extraction and here it is done by Convolutional Neural Networks (CNN). CNNs were created in order to automatically pick up organizational and discriminating characteristics from the raw input images. Small filters are convolved throughout the input image in a sequence of convolutional layers in order to gather regional patterns and characteristics. The boundaries, surfaces, and contours that make up the graphical world are captured by these features [22]. The feature maps are then down sampled by pooling layers, which reduces the computational burden while preserving crucial information. Fully connected layers receive the outcomes of the characteristics learned and use them for categorization or similar tasks in the future. With contemporary effectiveness in challenges like recognition of objects, segmenting an image, and image analysis for medicine, CNNs have achieved impressive results in a variety of applications that use computer vision. This is attributable to their capacity to spontaneously acquire and retain significant characteristics from images. The CNN-based multi-modal fusion technique harnesses the advantages of each method, making up for the limits associated with particular techniques and offering a more thorough understanding of the neurological state by combining data from various modalities. This comprehensive representation improves the model's capacity to provide more accurate and reliable diagnoses, allowing physicians to learn more about the condition of the patient and formulate effective therapies. The diagrammatic representation of CNN is depicted in Fig. 3.

E. Ensemble Learning

A machine learning technique known as ensemble learning integrates the projections of various designs, known as base learners and it is utilized to produce an end result that is more accurate and trustworthy. Ensemble learning tries to enhance efficiency, generalization, and dependability by utilizing the variety of distinct models [23]. The base learners may consist of multiple algorithms or modifications of the exact same algorithm that have been trained on various data groups. The ensemble aggregates its forecasts via techniques like vote by majority, weighted average or layering. Ensemble learning is utilized extensively over multiple fields, such as regression, classification, detection of anomalies and has been demonstrated to be highly efficient in solving complicated issues and producing better final results comparing to individual methods.

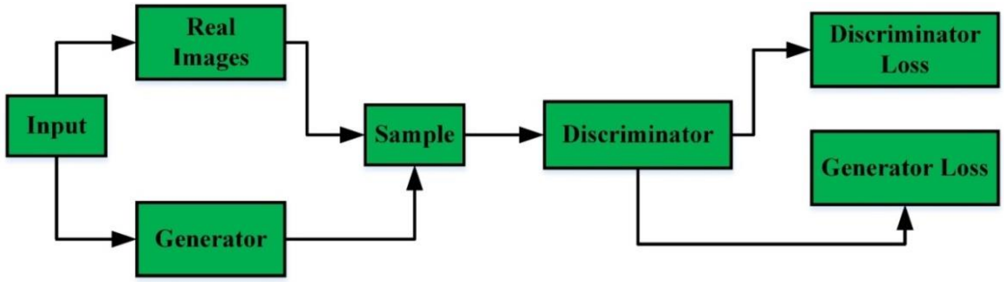

Fig. 2. Generative adversarial network.

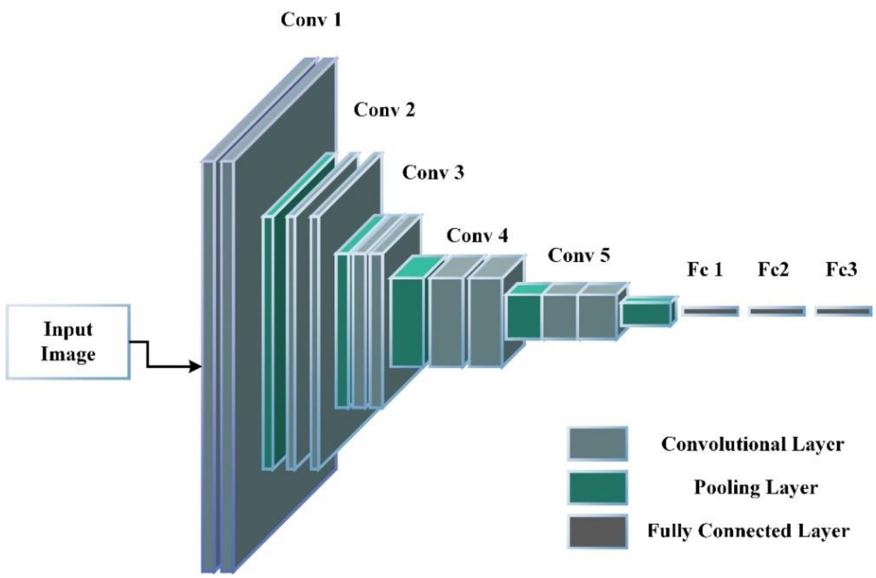

Fig. 3. Convolutional neural network.

1) Vote of majority: A straightforward and well-liked technique for merging the projections of base learners in the classification issue is the vote of majority. The classification for an input provided is predicted by every base learner in the ensemble and the final guess is the collective label that all base learners agree on. In the event of a tie, the category label having the greatest level of probability or likelihood will win. Although the base learners possess a low correlation and prone to engage in various errors, the vote of majority works well because it lessens the effect on particular errors.

2) Weighted average: In problems with regression where the base learners estimate constant outcomes instead of binary class labels, weighted average is frequently utilized. The ultimate prediction is derived by adding the weighted predictions after multiplying each base learner's forecast by the weight. The weights may be chosen independently or by using methods like the cross-validation or minimization.

3) Layering: The process of layering sometimes referred to as stacking, is a sophisticated ensemble learning technique that entails teaching a meta-model, or stacker, to draw knowledge from the forecasts of numerous base learners. Utilizing the provided data as a starting point, the base learners produce guesses; these hypotheses then serve as new characteristics for the meta-model. After learning via these preliminary estimates, the meta-model can subsequently anticipate the outcome. The utilization of stacking enables the ensemble to make the most of the abilities of various base learners and may enhance effectiveness. The algorithm of the proposed ensemble learning is given below and followed by that Fig. 4 depicts the flowchart of the proposed method.

Algorithm 1: Proposed CNN-GAN

Input: Multi Modal MRI Scan Image
Output: Diagnosis of Rare Neurological Disorder
Load data for provided image //Data Collection
Cleaning of data, Elimination of noise //Pre-processing
Data Augmentation, Medical Image Fusion //GAN
for G training L **do**
for D training N **do**
Select r patches from the testing data and generated data
G and D equation is given in (1)
Update Discriminator
Select r patches from the testing data
Update Generator
end for
Feature Extraction //CNN
Vote of majority, weighted average and layering //Ensemble Learning

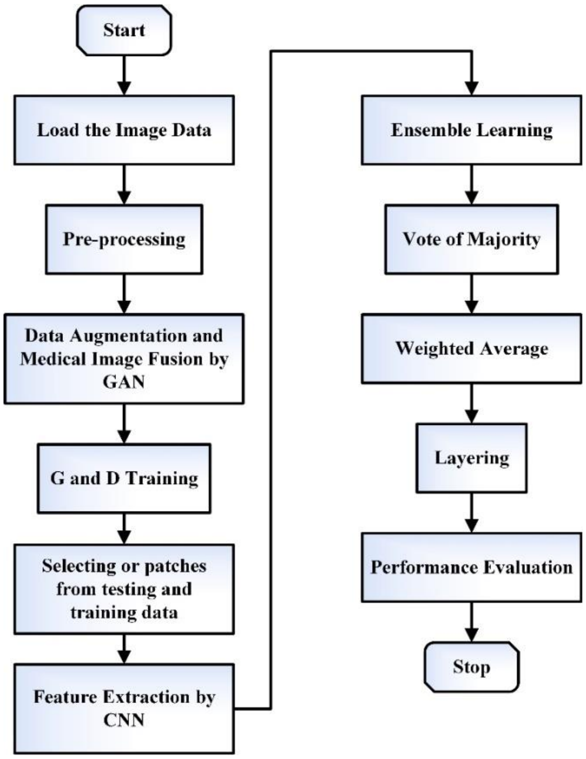

Fig. 4. Flowchart of proposed ensemble learning based CNN-GAN method.

V. Results and Discussions

The recommended method has been inspected by means of some datasets. Here, Ensemble Learning based Convolutional Neural Network and Generative Adversarial Network framework (CNN-GAN) is secondhand in this investigation for the diagnosis of multi modal fusion neurological disorders. Python is the programming language that was employed to construct and carry out the computational methods described in the suggested technique, which were executed utilizing Python software. The description of the recommended technique is reflected by certain features such as Accuracy, Recall, Precision, F1 Score, ROC, Training Accuracy and Training Loss.

A. Performance Metrics

1) Accuracy: The statistic that is the simplest to understand is accuracy, which is expressed as a proportion of all instances that occurred when a data set has been correctly classified. It provides a comprehensive indication of overall correctness. The accuracy calculation is offered in Eq. (2) below.

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \quad (2)$$

2) Precision: Precision is the ratio of exactly predicted favorable outcomes to all other instances. The precision equation is offered in Eq. (3) below,

$$Precision = \frac{TP}{(TP+FP)} \quad (3)$$

3) Recall: Remember to compute the proportion of correctly anticipated beneficial actions that actually materialized amongst all favorable situations. It increases up how well the algorithm can categorize every favorable circumstance. In Eq. (4), the recall formula is presented.

$$Recall = \frac{TP}{TP+FN} \quad (4)$$

4) F1 Score: Precision and recall are effectively added to create the F1 score. It combines both dimensions to provide a single number that provides a precise evaluation of a representation's effectiveness. In Eq. (5), the F1-Score equation is distributed.

$$F1 - Score = 2 \times \frac{(Precision \times Recall)}{(Precision+Recall)} \quad (5)$$

In Table I and Fig. 5 it shows the values of Accuracy, Precision, Recall and F1 Score of the existing i) XGBoost method [24] ii) LSTM method [25] and the proposed method produces more accuracy of about 99.99%, precision of about 99.13%, recall of about 98.21% and f1 score of about 98.99% than the existing methods.

TABLE I. Comparison Table of Accuracy, Precision, Recall and F1 Score

Method	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
XGBoost	85.69	57.62	63.21	60.22
LSTM	96.12	97.87	90.32	92.96
Proposed Method	99.99	99.13	98.21	98.99

B. Training Accuracy and Training Loss

The proportion of occurrences in the training dataset that were properly anticipated is known as training accuracy, and it shows the extent to which the model works on the data it was developed on. High training precision alone is not enough to guarantee effective generalization to new data because over fitting could lead to poor generalization. The difference among the forecasts made by the model and the actual goals achieved over training is quantified as training loss. By changing the parameters of the model, the goal is to increase the effectiveness of the model on the training data while minimizing the training loss. Considering optimization excessively for training data it can result in inadequate results on new, unforeseen data, finding a balance between low training loss and high generalization is a significant difficulty in machine learning. For the algorithm to produce precise forecasts on new information and to gauge its learning progress, it is critical to track both measures. Fig. 6 depicts the diagram of Accuracy vs. Loss graph.

C. Area under the ROC Curve (AUC-ROC)

A binary classification model's efficacy can be evaluated graphically utilizing the Receiver Operating Characteristic (ROC) curve. For the algorithm's predictions, it displays the true positive rate (sensitivity) versus the false positive rate (1-specificity) across different threshold values. The ROC curve enables users to see the trade-off among the model's tendency to attribute negative examples wrongly and its capability of correctly recognizing positive instances.

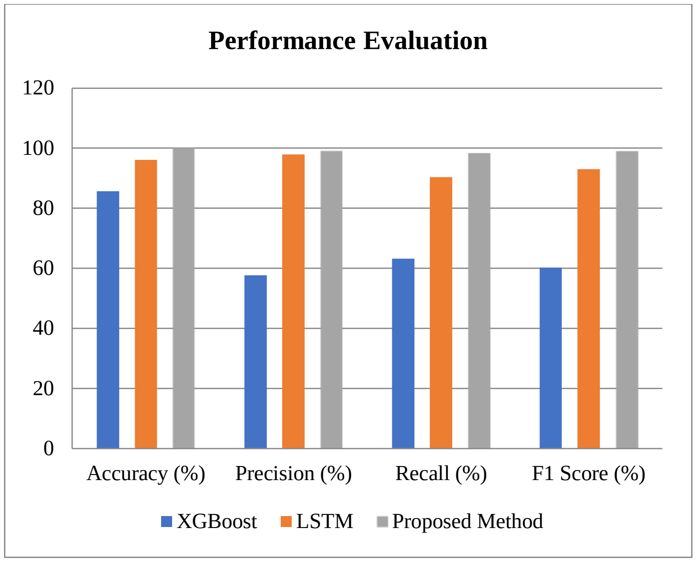

Fig. 5. Comparison graph of accuracy, precision, recall and f1 score.

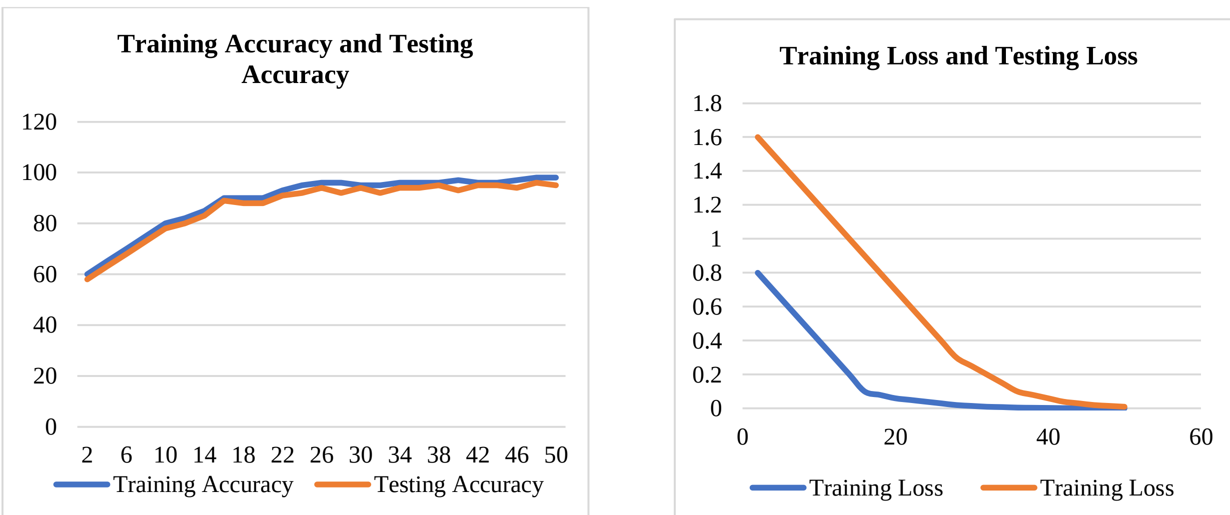

Fig. 6. Accuracy vs loss.

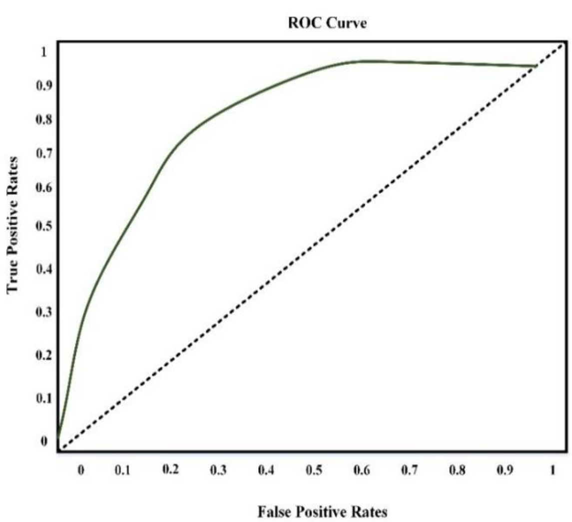

Fig. 7. AUC-ROC.

An ROC curve that crosses the top-left corner of the plot, which denotes a high degree of sensitivity with a low false positive rate, represents the ideal classifier. An AUC-ROC number below 1 implies high classification abilities, while a value near to 0.5 denotes random or poor performance. The area under the ROC curve (AUC-ROC) is an individual scalar statistic calculated from the curve that provides an overview of the model's general efficacy. ROC analysis is utilized frequently in machine learning to evaluate and contrast the performance of classifiers in a variety of programs, including detecting fraud, identifying anomalies, and medical diagnosis and its diagram is depicted in Fig. 7.

D. Discussions

The cumulative corpus of research highlighted highlights the changing face of neurological healthcare, with a focus on the amalgamation of cutting-edge technologies and artificial intelligence (AI). Khan et al. address the growing difficulty of diagnosing and treating an increasing range of brain illnesses, arguing for the central function of the cerebral cortex as the body's centre of control. The potential transformative influence on diagnostic and treatment precision is highlighted by their investigation of AI applications, particularly in machine learning and deep learning, for the early detection of illnesses like Parkinson's, seizures, brain tumours, and Alzheimer's. Musallam, Sherif, and Hussein [12] offer insightful observations about the connection between neurological illnesses and abnormal brain cell growth. They also suggest a unique Deep Convolutional Neural Network (DCNN) that can be used with advanced pre-processing techniques to improve tumour identification. On the other hand, there is still a significant drawback in the proper diagnosis of many disorders from magnetic resonance imaging (MRI) images. The investigation by Hashem et al. [13] of the relationship between the neural system and the oral cavity emphasizes the importance of oral surgeons in identifying orofacial symptoms of neurological disorders. Although the significance of state-of-the-art techniques for comprehensive assessment is emphasized, the restriction is the narrow emphasis on preventive dental care approaches, which may obscure more general dental health issues. Although novel, the use of the Internet of Medical Things (IoMT) to dentistry is criticized for its restricted focus on preventative maintenance, especially when it comes to detecting tooth decay. Ning et al.[14] 's proposal to integrate multi-modal data for Alzheimer's disease detection tackles the issue of overfitting in highly dimensional data. Deep learning for the purpose of classifying attack patterns in cerebral implants is being investigated by Rathore et al. [15] their work highlights issues with labelled information accessibility, patient-to-patient variability, and the critical need for accuracy, comprehension, and security considerations, including patient privacy. With an emphasis on epilepsy detection, Zhang et al.[16] expose the shortcomings of methods that rely on patient history data and present a deep neural network architecture that is highly intelligent and can learn from epileptic episodes to improve seizure diagnosis. As a whole, these studies highlight the exciting possibilities that artificial intelligence (AI) and technical advancements hold for improving neurological healthcare. However, they also highlight ongoing obstacles that require additional study and improvement before being put into practice.

A novel ensemble learning approach for precise feature extraction and feature fusion from multi-modal medical images to identify uncommon neurological illnesses is suggested in this research. Convolutional neural networks (CNNs) and generative adversarial networks (GANs) are utilized in the suggested strategy in a CNN-GAN combined strategy, with the goal of improving the diagnostic precision and enabling rapid diagnosis. In a broad collection of multi-modal health records, crucial clinical data is effectively combined from multiple approaches by constructing artificial images via GAN-based translation. The assessment of the method's robustness and reliability are increased by the ensemble technique, which employs voting by majority, weighted average, and stacking to combine estimates in order to arrive at the ultimate diagnosis. As a result, it is more effective in identifying unusual neurological illnesses. The technique functions better than single-modal concepts showing the significance of multi-modal fusion of images and feature extraction, possibly offering a quick and reliable detection of unusual neurological disorders, with a combined approach resulting to about 99.99% diagnostic accuracy. To verify the generality and usefulness of this suggested strategy in actual clinical circumstances, further verification on a bigger and more varied dataset will be required.

VI. Conclusion and Future Works

Convolutional neural networks (CNNs) and generative adversarial networks (GANs) are being combined in this study to improve diagnostic accuracy and enable early detection. In order to diagnose unusual neurological illnesses, this work offers a unique ensemble learning technique that successfully mixes and segregates characteristics from multi-modal medical pictures. Critical health data is effortlessly incorporated from diverse medical records using GAN-based translation. The research extracts distinguishing characteristics from sizable clinical imaging databases by utilizing transfer learning inside specialized CNN frameworks, giving a thorough knowledge of the basic pathophysiological concepts. Voting, weight averaging, and stacking ensemble approaches all effectively include hypotheses, greatly improving the identification of uncommon neurological illnesses. With a diagnostic reliability of over 100%, this combination strategy performs better than single-modal approaches. This novel approach has a great deal of promise to transform medical image processing, possibly enabling quick and precise diagnosis, and eventually enhancing patient outcomes. But further testing and real-world applications are necessary. Future research can broaden the ensemble learning strategy to incorporate more sophisticated fusion methods and apply it to different medical specialties. Comprehensive research studies and validation across a larger and more varied patient group are necessary to evaluate the method's practical efficacy and generalizability.

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