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***Abstract:** In the medical area, computer-aided detection through machine learning (ML) and deep learning (DL) is rapidly expanding. Medical pictures are thought to be the real source of the relevant data needed for disease diagnosis. One of the most crucial things to reduce the death rate from cancer and tumours is early disease detection utilising a variety of modalities. Radiologists and medical professionals can better understand the internal anatomy of a discovered disease by using modalities to extract the necessary features. Large data sets limit ML's ability to use current modalities, however DL is capable of handling any volume of data with ease. As a result, DL is seen as an improved method of ML, in which ML makes use of learning strategies and DL gathers information about how machines need to behave in human environments. To obtain more details about the datasets that are used, DL makes use of a multi-layered neural network. The purpose of this study is to provide a comprehensive assessment of the literature on the use of ML and DL for the identification and categorization of various diseases. An extensive analysis was previously conducted, and it offers a summary of several methods based on ML and DL for the identification and categorization of various illnesses, medical imaging modalities, instruments and procedures for assessment, and dataset descriptions. By enabling medical professionals and researchers to select an optimal diagnosis technique for a certain condition with high accuracy and minimal time, this work will benefit the healthcare community.*

***Keywords:** Healthcare, Medical image processing Machine learning, Deep learning*

1. INTRODUCTION

It is possible to see the importance of illness classification and prediction from prior years. To pinpoint the precise source of an illness as well as its symptoms, it is imperative to be aware of the crucial characteristics and attributes provided in a dataset. Artificial intelligence (AI) has proven capable of both classification and decision support. A subset of AI called ML has sped up a lot of medical research. On the other hand, DL is a branch of ML that works with neural network layers to analyse the precise information needed for disease identification [1]. Finding the ideal arrangement of crucial information and removing unnecessary ones is difficult since AI evaluates a dataset using a range of techniques to extract the essential features or highlights from a vast amount of data. Including these elements is inconvenient and leads to erroneous accuracy measures. Consequently, the efficiency of the model will increase when a limited subset of a wide range of features is chosen. The removal of cumbersome and repetitive features would thereby reduce the dimensionality of the data and accelerate the trained model in a manner akin to boosting. To identify cancer sickness, a number of techniques were applied, such as feature selection, image segmentation, and regression using Root Mean Square Error (RMSE). Using six classifiers and transfer learning (TL) approaches for brain magnetic resonance imaging (MRI) image segmentation, a brain tumour was identified [2]. Moreover, a TL method was used to diagnose brain illness and lung cancer. Support Vector Machine (SVM) classifiers trained through supervised learning were used to analyse MRI and CT scan pictures [3]. The extant literature provides a thorough understanding of the image analysis procedure. On the other hand, ML and DL techniques are always evolving. This review is important because it will empower medical professionals to employ ML or DL techniques for accurate and dependable disease detection, classification, and diagnosis. It will also help academics and doctors avoid misinterpreting datasets, develop effective illness detection algorithms, and provide knowledge about the various contemporary medical imaging modalities of ML and DL.

2. BACKGRAOUND STUDY

Many studies conducted in the past have concentrated on developing predictive models for ED tendencies. These studies' feature categories include structured data (like age, gender, etc.) and unstructured data (like chief complaints, nursing notes, etc.). Numerous research in this series only use structured data to predict ED dispositions. Nonetheless, there are comparatively fewer research that use unstructured data exclusively or combine unstructured and structured data to predict ED dispositions [4]. For example, Lucini et al. used only unstructured medical records that were converted into characteristics using natural language processing in order to forecast the likelihood that emergency patients would be admitted [5]. With an F1-score of 77.7%, the support vector machine had the best performance, according to the data. This study's strength is how well it shows how ML works with unstructured data. Additionally, Lucini et al. examined the performance outcomes of their models after testing them with seven different methods [5]. One obvious drawback is that they did not account for other ED dispositions; instead, they only predicted hospital admissions and non-hospital admissions. Hayori et al. [10] discovered that a deep neural network (DNN) could predict hospitalisation of patients with an accuracy of 0.83 and an area under the receiver operating characteristic curve (AUROC) of 0.88 by using triage notes. This study does a great job processing triage notes using the Bidirectional Encoder Representations from Transformers approach. Like Lucini et al., Taha-yori et al. did not investigate additional ED dispositions; instead, they concentrated only on predicting patient admission or homestay [5-6].

Additional instances, like the research done by Zhang et al. [7], combined demographics and ED visitation motives to forecast the probability of hospitalisation for the patient. This was accomplished by creating predictive models using DNN in addition to logistic regression. According to the findings, models that included structured and unstructured data fared better than those that just used one type of data. This study's use of both structured and unstructured characteristics in the model development process is noteworthy. To further demonstrate the effectiveness of these various feature types, Zhang et al. [7] examined the performance of models using structured, unstructured, and blended data. One drawback is that they don't look into other potential ED dispositions; instead, they just forecast admission or transfer. Duanmu et al.'s [8] use of both structured and unstructured data to create their model is indicative of the study's value; of particular note is their utilisation of chest X-rays rather than free-text reports. It is nevertheless crucial to remember that they ignored other possible outcomes in favour of concentrating only on forecasting incidences of death or non-mortality. Demographics, vital signs, lab results, and chest X-rays were utilised by Duanmu et al. [8] to forecast ED patient death. According to the study's findings, models that combined structured and unstructured data showed better predictive power than those that used only one type of data, with higher AUROC and accuracy.

We gain a better grasp of unstructured data's predictive power for ED disposition from these research that use it to predict ED disposition. These current results point to a number of avenues for future research that may improve ML's capacity to predict ED disposition. First off, most studies use binary class approaches to construct predictive models; only a small number of studies use a multiclass strategy to predict various ED dispositions at the same time [9]. Practically speaking, the key feature should be the capacity to anticipate various ED dispositions in a straightforward and thorough way, without the need for separate prediction models for each disposition. Second, considering the importance of this topic, further research is required to further consolidate knowledge on the application of ensemble learning approaches in predicting ED dispositions, even though research has started to examine this usage. Given that ensemble learning performs well [10], using it to develop predictive models of ED disposition may reveal the full potential of the technique.

3. MEDICAL IMAGE ANALYSIS

Medical image analysis is a crucial field within healthcare that involves the processing, interpretation, and extraction of information from various types of medical images. These images can come from modalities such as X-ray, MRI (Magnetic Resonance Imaging), CT (Computed Tomography), ultrasound, PET (Positron Emission Tomography), and histopathology slides. Medical image analysis plays a vital role in diagnosis, treatment planning, and monitoring of diseases and conditions across different medical specialties, including radiology, oncology, cardiology, neurology, and pathology. The process of medical image analysis typically involves several key steps: Image Acquisition, Image Pre-processing, Segmentation, Feature Extraction, Classification and Diagnosis, Visualization and Interpretation. The ailments that are covered by the current literature review are broken down into categories, including diabetes, brain tumours, lung diseases, breast cancer, and multiple disease detection.

3.1 BREAST DISEASE

Articles on the use of ML and DL techniques for breast disease diagnosis, detection, classification, and prediction are covered in this part. Using BI-RADS (Breast Imaging Reporting and Data System), important aspects were found in [11] to create a CAD system for getting breast ultrasounds. Also, a 10-fold cross validation process was applied to the benign and malignant lesions. Consequently, the SVM classifier yielded results with an accuracy of 77%. But certain approaches that handle the wide range of data with a few algorithms require careful understanding and analysis [12]. CNN was utilised to understand the intricate structure and train the system using the clinical data that was accessible. DL methods with the algorithm's architecture and several ML methods for image processing were covered. The examination of different images, including histology, thermography, mammography, ultrasound, and MRI images, utilising the CAD system was investigated in order to research the technologies. Additionally, ML techniques including SVM, ANN, DT, Naive Bayes, K-Nearest Neighbour (KNN), etc. were implemented in the system.

3.2 BRAIN DISEASE

In order to partition the brain's MRI scan using voxel-wise categorization, the notion of TL was applied [7]. A variety of disorders were classified using ML classifiers. The disease was later identified by comparing the acquired results with the pre-existing data. In [13], a succinct overview of DNN in medical image analysis for brain tumour diagnosis using brain tissues is given. It demonstrated how to use DL throughout the MRI scanning, picture retrieval, segmentation, and disease prediction processes. Additionally, it concentrated on feature segmentation and illness prediction as well as picture acquisition to image retrieval. Two elements comprised the complete procedure: (i) MRI signal processing, which included image restoration and image registration; and (ii) employing DL to produce prediction-based text and image reports for disease detection. [14] also addressed the effect of DL on medical imaging. DL was employed in a number of image segmentation approaches, including the segmentation of tumours and the usage of bone tissues or cells to represent the structure of the brain and lung. The input patches were pre-processed using the 2-Dimensional Convolutional Neural Network (2D-CNN) at a later stage.

3.3 LUNG DISEASE

By weighing the benefits and drawbacks of various DL algorithms, DL can automate the picture interpretation process, improving clinical decision making by diagnosing the condition and forecasting the patient's optimal course of therapy [15]. These methods were used to the cardiovascular drug; the processes to apply the DL model are as follows: the identification of the issue, the selection of data, the choice of hardware and software, the preparation of the data, the selection of features, and the division of the data for the training and validation processes. In [16], DL models were used to process medical photos in order to obtain accuracy in an automatic analysis of an illness utilising labelled data. In order to identify trends, the autonomous illness prediction employing ML techniques and the big data idea was compiled [17]. Every algorithm's benefits and drawbacks were also covered.

3.4 DIABETES

Using an iridology chart, a comparative study of the iris image-based classification algorithms was conducted for the diagnosis of diabetes [18]. By assessing the pupil's centre of vision, type-2 diabetes was detected early on with the I-Scan-2. Furthermore, a filter-based feature selection method was paired with five classifiers: binary tree, SVM, neural network model, Random Forest (RF), and adaptive boosting model. Later, in [19], a study was put together to identify the same condition utilising the 62 iris features (textural, statistical, and varied aspects); an iridology chart was not utilised in this investigation. The faults in the current diagnostic systems were identified using ML and DL algorithms [20,21]. These methods were used to medical image analysis in order to extract the features needed to diagnose problems in the diagnostic systems that are now in use. In certain datasets, algorithms that were both supervised and unsupervised were utilised to predict the disease. It has been noted that the DL approach is far more effective at analysing medical photos [22]. For the right decision-making, a variety of approaches were applied, including object identification, pattern recognition, and image categorization. Because it could anticipate an illness's early signs, medical treatments were enhanced. In order to educate upcoming researchers, a summary of ML and DL methods utilised in the medical profession was also provided. Using self-created data, methods such rubber sheet normalisation, ML classifiers, PCA, etc. were applied in [23] to compute six parameters for reliable Type-2 diabetes prediction: (i) accuracy, (ii) sensitivity, (iii) specificity, (iv) AUC, (v) precision, and (vi) F-score.

3.5 MULTIPLE DISEASE DETECTION

Different radiography techniques, such as CAD for breast cancer coupled with skin lesions, MRI imaging for breast cancer along with brain tumour, and X-rays for chest examination, were used to identify many diseases [24]. Additionally, ML approaches were employed to improve accuracy while denoising using wavelet, non-homomorphic, soft, and homographic wavelet thresholding. To help radiologists, a CNN-based CAD system for classifying breast tumours as benign or malignant was developed [25]. The Automated Breast Ultrasound (ABUS) pictures were processed to extract multiview features using the Inceptionv3 framework. 316 data sets with breast lesions were assessed and trained in preparation for the model's deployment. When the proposed approach and the ML feature extraction methodology were compared, the AUC value increased by 10%. A review of picture fusion was given in [26], which enhanced the quality and decreased the unpredictability of the images that were available. A summary of the many approaches and difficulties involved in picture fusion was also provided [35-39]. Small labelled datasets were the focus of ML and DL algorithms in [27], since they were thought to be crucial in decision making. The benefits and drawbacks of several ML algorithms were also examined in relation to noisy data in medical imaging.

By identifying patterns in the available data and subsequently classifying the diseases using ML classifiers, a number of diseases, including diabetes, heart disease, liver disease, dengue, and hepatitis, were found [28,29]. To precisely anticipate the diseases, it made use of multimodal and high-dimensional datasets. Using ML approaches such as ML pipelines and classifiers with baseline variables from MRI imaging, the patient's declining state was predicted. A description of DL tools for pattern identification and prediction in AI applications for medical imaging may be found in [30]. Apart from AI methods, ANN and CNN were also helpful in forecasting the disease by examining the pattern in the images, and classifiers could be used to classify the disease [31]. In order to identify errors in the diagnosis system, a number of algorithms were examined, suggesting the significance of ML and DL for early disease identification [32]. On the other hand, [104] talked about the three primary difficulties: (i) handling image variances; (ii) learning from faulty labels; and (iii) accurately interpreting the results for the diagnosis of cancer using the provided medical images. It was determined that TL was employed to handle variances in images. To overcome the poorly labelled data and increase the accuracy of the disease classification for improved medical outcomes, weighted TL and the Multiple Instance Learning (MIL) approach were applied, respectively. It was recommended that rather than learning about each specific instance, one should understand the relationship between picture label and image collection.

4. CHALLENGES

Medical imaging technologies, such as X-rays, MRI, CT scans, and ultrasounds, generate vast amounts of data essential for diagnosing and treating diseases. ML and DL techniques have revolutionized this field by automating and improving the accuracy of image analysis. However, the transition from research to clinical application is fraught with challenges. Addressing these challenges is crucial for the widespread adoption and efficacy of these technologies in healthcare.

4.1 DATA RELATED ISSUES

High-quality, annotated datasets are crucial for training ML and DL models. However, obtaining such datasets is challenging due to several factors:

Limited Availability: Large, labeled datasets are scarce, particularly for rare diseases. Annotation requires expert knowledge, making it time-consuming and expensive.

Data Imbalance: Medical datasets often have an imbalance, where certain conditions or classes are underrepresented. This imbalance can lead to biased models that perform poorly on minority classes.

Data Privacy and Security: Patient data is sensitive, and sharing it for model training is restricted by privacy laws such as HIPAA and GDPR. Anonymizing data can help but might not always be feasible or sufficient.

4.2 MODEL INTERPRETABILITY

DL models, particularly deep neural networks, are often considered black boxes due to their complex architectures. In a medical context, interpretability is critical for:

Clinical Trust: Clinicians need to understand and trust the model's decision-making process to rely on its outputs for diagnosis and treatment.

Regulatory Approval: Regulatory bodies require explanations of how models work and make decisions, especially for high-stakes applications like disease diagnosis.

4.3 COMPUTATIONAL RESOURCES

Training DL models requires significant computational power and memory. Challenges include:

Hardware Limitations: Not all medical institutions have access to high-performance computing resources like GPUs and TPUs necessary for training and deploying large models.

Energy Consumption: The energy demands of training deep models are substantial, raising concerns about sustainability and cost, especially for institutions in resource-limited settings.

4.4 REGULATORY AND ETHICAL CONCERN

Deploying ML and DL models in clinical practice involves navigating complex regulatory landscapes:

Approval Processes: Medical devices, including software for image analysis, must undergo rigorous testing and approval by regulatory bodies like the FDA and EMA. This process can be lengthy and costly.

Ethical Issues: Ensuring fairness and avoiding biases in ML models is crucial to prevent disparities in healthcare. Additionally, there are concerns about data ownership, consent, and the potential misuse of AI in healthcare.

4.5 INTEGRATION INTO CLINICAL WORKFLOW

For ML and DL models to be useful in clinical settings, they must be seamlessly integrated into existing workflows:

User Interface and Experience: Clinicians need user-friendly interfaces that provide actionable insights without disrupting their workflow.

Real-Time Processing: Many applications, such as intraoperative imaging, require real-time analysis, which current models and computational infrastructure may not support effectively.

Interoperability: ML and DL systems must be compatible with various medical record systems and imaging devices, which can vary widely across institutions.

5. IMAGING MODALITIES

ML classifiers such as SVM, RF, and NB were utilised in combination for classification. Neural networks, such as CNN or ANN, were used for detection, and TL was often used because of its capacity to deconstruct enormous datasets. The percentage of various disorders diagnosed in the primary investigations is shown in Figure 1. As can be seen, breast cancer has the greatest percentage (21%) of all diseases and is the most prevalent. In second place (18%) were brain tumours, followed by lung disease (16%) and diabetes (16%). Moreover, a number of methods were used to diagnose conditions affecting the eyes, liver, skin, hepatitis, and cancer. The percentage of different approaches employed in primary investigations is shown in Figure 2.

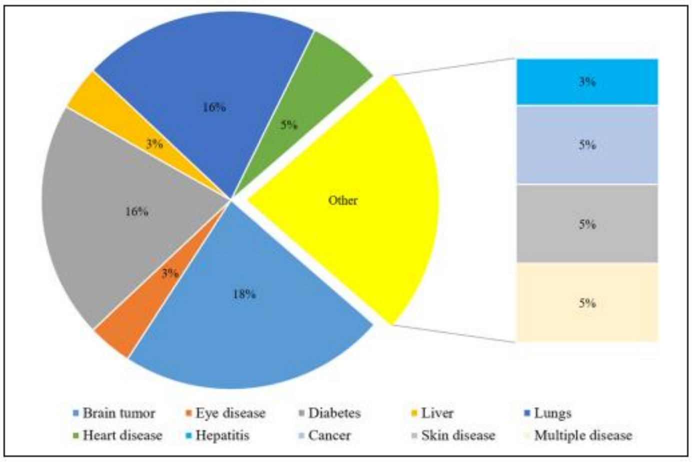

Fig.1. Disease percentage

In summary, SVM (20%) is the method most frequently utilised for classifying medical images. Fig. 3 shows the statistical analysis of ML and DL methods for medical diagnosis. The many visual modalities used to assess medical images are shown in Figure 4. However, with 45% of the subject, MRI/X-ray dominates. With 30% of uses, CT-Scan is the second most used modality, after mammograms (10%) and I-Scan-2 (10%). Additionally, computer modalities like CAD were added for the detection of cancer and hepatitis in order to automate the process of retrieving and analysing the features [33,34].

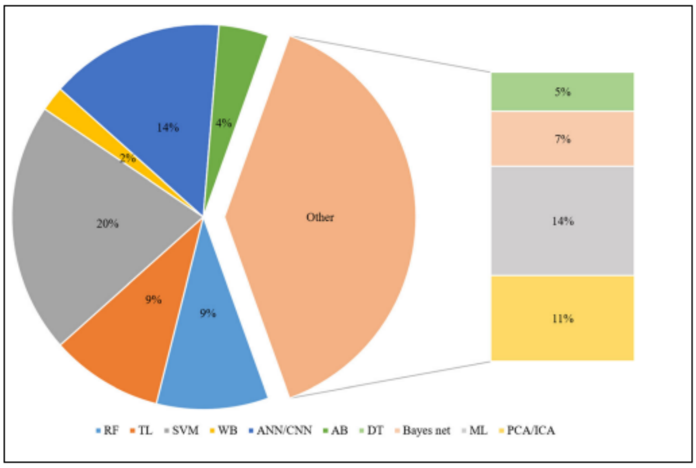

Fig.2. In healthcare percentage of ML and DL techniques

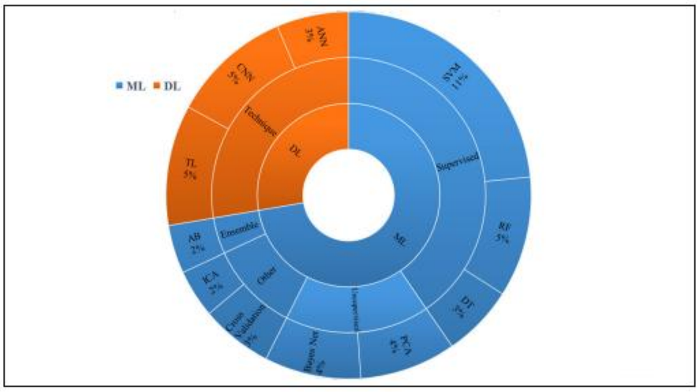

Fig.3. Statistical analysis of medical diagnosis using ML and DL techniques

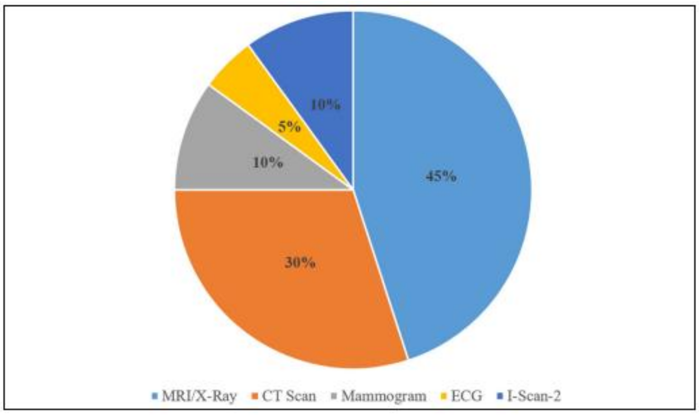

Fig.4. In medical imaging percentage of modalities used

6. CONCLUSION

While ML and DL offer significant potential for advancing medical image analysis, addressing these challenges is essential for their successful integration into clinical practice. Collaborative efforts among researchers, clinicians, regulatory bodies, and technology developers are needed to overcome these barriers. Future research should focus on developing more interpretable models, improving data sharing mechanisms, optimizing computational efficiency, and ensuring ethical and regulatory compliance. This paper presents an overview of different ML and DL approaches for illness detection, covering categorization, imaging modalities, tools, algorithms, datasets, and medical domain issues. The most often utilised modalities for diagnosing diseases are MRI and X-ray scans. Furthermore, MATLAB and SVM, respectively, dominated all the tools and approaches tested. It was noted that researchers make extensive use of the MRI dataset. CNN (97.6%) and RF (96.93%) have surpassed other methods in a comparative examination of ML classifiers and DL models, which was conducted through a series of tests using the MRI dataset.

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