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Deep Learning Approaches for Medical Image Analysis and Disease Diagnosis

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ABSTRACT

Propose: Today, there has been a major global advancement in medical image-based diagnosis. A great deal of research is being done in this area, and the results are having a big influence on mankind. In this industry, the volume of data being generated and stored in databases is rapidly increasing. It is important to examine this data to identify significant underlying trends. Classification is a useful technique for spotting these trends..

Aim: In comparison to conventional methods, deep learning models possess the potential to identify intricate patterns and characteristics in medical photographs. This capability could lead to significantly more accurate diagnoses, potentially revolutionizing the field of medical image-based diagnosis.

Method: This study suggests an extensive investigation and evaluation to assess and diagnose health photographs using different categorization techniques and seriously evaluate those methods' efficacy. Artificial Neural Networks (ANN), Support Vector Machines (SVM), K-Nearest Neighbours (KNN), Decision Trees (DT), Random Forests (RF), Naïve Bayes (NB), Logistic Regressions (LR), Random Subspaces (RS), Fuzzy Logic, and a Convolution Neural Network (CNN) model of Deep Learning (DL) are some of the machine-learning (ML) procedures used for categorization.

Results: The aforementioned methods were applied to two distinct datasets: chest X-rays, used to categorize lung images as normal or abnormal, and melanoma skin cancer dermoscopy, used to categorize skin lesions as benign or dangerous. In an effort to categorize medical databases while comparing various approaches to determine the most reliable and effective diagnosis, this study introduces a novel framework. This framework aims to facilitate the investigation and evaluation of Machine Learning (ML) methods and DL utilizing CNN, marking a significant advancement in the field.

Conclusion: Our findings demonstrate the effectiveness of the used categorization strategies in terms of performance metrics.

Keywords: Medical Image, Classification Algorithms, Skin Cancer, Performance Measures, Medical Databases, Diagnose, Deep Learning (DL).

INTRODUCTION

Diabetes Mellitus (DM) incidences have significantly grown during the last 20 years in public health systems around the world. Approximately 30, 177, and 185 million cases occurred in 1985, 2000, and 2010, respectively. According to epidemiologic research, by 2030, there will likely be more than 360 million DM sufferers worldwide. Diabetes mellitus (DM) patients can experience a variety of problems, including diabetic foot ulcers (DFUs), a condition that has been on the rise in recent decades. It is estimated that approximately 15% of diabetics have DFU in their lifetime [1].

Accurate DFU frequency statistics are difficult to obtain, although they may vary from 4 to 27%. DFU is now the most prevalent form of morbidity in persons with diabetes and is considered a main source of hospitalizations. Around twenty percent of hospital admissions with DM had DFU, as expected [1, 2].

More specifically, there is a higher chance of ulcer development when a patient has DFU, which could eventually cause potation. A single ulcer surgical procedure costs around $17,500, based on previous investigations.

If all expenditures are taken into account, DFU may account for between 7 and 20% of the general diabetes spending in Europe and North America. A number of essential tasks for early diagnosis, monitoring progress, and various regular procedures for DFU management and therapy, depending on each case, make up the evaluation procedure for DFU. This assessment procedure consists of:

- Assessing the patient's past medical records,
- Assessing the DFU with a diabetic foot expert and
- Adjunctive diagnostics like X-rays,

Treatment plan development may benefit from Computed Tomography (CT) and Magnetic Resonance Imaging (MRI). Therefore, to assess visual appearances such as textures, characteristics, or color descriptors, Computer Vision (CV) techniques are required. Cancer develops and causes lumps and tumors. Still, certain oddities may not be dangerous. An examination under a microscope takes place by the physician to assess if a lump or tumor is malignant. It is called a benign tumor because it is not malignant [2, 3]. Other than tumors, malignancies may also affect other bodily cells, such as platelets or leukemia, which is a blood disease.

Starting breast cancer cells is inappropriate for cell development. Tumors often have repeating knots or x-beams comprising these cells. If the cells in a tumor divide into new, more powerful components or propagate throughout the body, they may become dangerous (diseases). Breast cancer may spread to different regions of the breast. Most breast cancers start in the milk-producing channels and then go to the areola. Some come from the organs that produce milk. There are many ways that breast cancer may develop, some of which are more frequent than others. Certain types of breast cancer have their origins in different tissues. Breast cancer causes the breasts to protrude, even though there are many different forms of the disease. Numerous breast diseases may be identified via mammography screening [3, 4]. This helps solve problems before they happen.

Mammography produces an X-ray picture of the breast. Thanks to computerized mammography, tumor screening techniques no longer need repeat scans. Potential areas of interest for DM might include computer-based PC programs that alert radiologists to optimal differences in mammograms and permit integrated film misleading.

The computer-assisted design framework may be utilized to categorize malignant growth of the breast and lung, including colon polyps. Nevertheless, these modalities may still be used in case the master human beings population is not present [4, 5]. Computer-aided design framework displayed regions that seemed abnormal to radiologists based on a combined evaluation of patient drawings. Understanding that CAD might operate differently based on the settings means that any required modifications are done to get maximum accurate results.

Numerous advanced prognostic and diagnostics image-based biomarker extraction techniques for cancer have been established due to this [5, 6]. More specifically, the goal of medical image processing is to extract imaging biomarkers that can pinpoint patient groups suitable for personalized medicine strategies by interpreting individual variations in imaging phenomenology.

The primary need for quantifiable biomarkers in clinical settings has always been their precision and reproducibility. If these prerequisites are satisfied, image biomarkers may help physicians better plan individualized treatment and evaluate the pathophysiologic alterations in their patients [7, 8]. This is significant because subjective characteristics (such as average heterogeneity, hypothesized bulk, and necrotic core) may be used in clinical settings and may reduce the accuracy of diagnostic procedures.

The aforementioned factors suggest that the identification of quantitative indicators that describe shape, dimension, flavor, texture, and activities may improve the diagnostic and therapeutic response evaluation capabilities of medical imaging. However, in cancer patient care, only more basic imaging metrics—like linear—are often used, [8, 9], particularly when assessing solid tumor response to therapy (such as a greater lesion dimensions in RECIST).

The evaluation requirements set by the WHO and RECIST were initially designed for cytotoxic treatments and rely on measures from anatomical images, typically obtained from CT or MRI data. However, these linear metrics are not without their limitations. Studies have shown inter-observer RECIST variation of up to 30%, indicating significant intra/inter-observed variability. This can potentially hinder the accurate evaluation of tumor response in certain scenarios.

According to a number of studies, 3D quantitative response assessments have a stronger correlation with the advancement of the condition than evaluations based on 1D linearity measures. Nevertheless, [10, 11], evaluating the response to more recent chemotherapy for cancer, such as determined anti-angiogenic medicines and immunotherapies, has proven to be very challenging for conventional tumor quantification methodologies employing linear or 3D tumor measurements.

Because they need a well-equipped setting and the participation of qualified professionals, conventional diagnosis techniques are expensive and time-consuming. The effectiveness and precision of computerized diagnostic solutions have grown recently, and these developments are quite promising [12, 13]. Our ability to apply medical image-processing methods to pictures of skin cancer with melanoma dermoscopy and chest X-rays will help diagnose illnesses sooner and more correctly, potentially saving many lives. The rapid development of computing and technology has made it possible to identify two diseases faster: lung cancer and skin cancer caused by melanoma.

Recently, medical research and image processing have both seen excellent outcomes from machine learning and deep learning approaches. Machine-learning algorithms have been used effectively in many healthcare domains. Many academics have proposed Artificial Intelligence (AI)-based therapies for various illnesses in recent years. Researchers have completed several medical applications with the help of the CNN technique and DL, including the classification of skin cancer from skin scans and the prediction of illness from X-ray images [14, 15]. Owing to this advancement, much research has been done to ascertain how DL and ML can impact the medical imaging diagnostics industry.

Teaching an electronic device to solve a problem by drawing on its existing knowledge is known as Machine Learning (ML). The idea of using ML in numerous domains to solve problems faster than humans has drawn a lot of attention since it is now possible to acquire cost-effective memory and processing power. This makes it possible to analyze enormous volumes of data to find patterns and insights that the human eye would miss. Numerous algorithms underpin its sophisticated actions, which enable the computer to generate notable findings.

DL, on the other hand, is a subsection of ML that offers a more sophisticated method that imitates how humans learn and think to enable computers to automatically extract, evaluate, and comprehend pertinent information from raw data. DL is a collection of neural data-driven techniques built on autonomously featured construction methods. Its ability to automatically learn input features accounts for its accuracy and performance. CNN is one of the best picture identification and classification models in deep neural networks [16].

In the present research, we analyze healthcare photos for two sets of healthcare databases, such as images from skin dermoscopy, which are used to identify skin cancer melanoma, and images from chest X-rays, which are used to detect lung disorders [17, 18]. In order to demonstrate the efficacy and efficiency of these techniques in categorization and diagnosis in medicine, we concentrate on using convolutional neural networks and the most popular machine-learning techniques for deep neural network training to categorize wounds on the skin in the second healthcare dataset as benign and malignant, and lung lesions in the first medical dataset as normal and inappropriate.

The main objective of this study is to compare and evaluate CNN and ML algorithms for the categorization of medical forms of databases and to find the ways that perform most successfully in diagnosis [19, 20]. We used these techniques to detect two separate diseases that are among the most serious, endanger human life, and have treatable forms if detected early on in the course of treatment.

Objectives of the Study

- To guarantee reliable performance in real-world situations, evaluate the deep learning models' capacity to generalize across various patient demographics, imaging techniques, and healthcare environments.
- Conduct comparison studies against current methodologies to evaluate the clinical value of approaches based on deep learning and their effect on patient outcomes, healthcare expenditures, and workflow efficiency.
- To guarantee reliable performance in real-world situations, evaluate the deep learning models' capacity to generalize across various patient demographics, imaging techniques, and healthcare environments.

LITERATURE REVIEWS

(Pandya, M. D., 2019) [21] The medical and wellness industries are quite different from the others. Consumers in these sectors need more affordable services of greater quality. Health or healthcare professionals are often the ones who analyze medical data. The three most common data formats used in the field of medicine are biological signaling (ECG, EEG, etc.), medical photographs (CT, MRI, etc.), and omics (DNA, RNA, etc.). Prejudice, picture complexities, fatigue, and the wide range of differences among interpreters all contribute to the limitations of medical image data as it relates to human professionals. The job is quite complicated when it comes to machine learning.

(Chen, X., 2022) [22] In order to create revolutionary medical imagery processing algorithms, deep learning has drawn a lot of attention from researchers. Deep learning-based models have shown remarkable performance in a range of medical imaging tasks that enable illness identification and diagnosis. Notwithstanding their achievements, the absence of substantial and meticulously annotated datasets significantly impedes the advancement of models using deep learning in the field of medical image analysis.

Numerous research have addressed this topic in the last five years. We analyzed and compiled these current works in this publication to provide a thorough overview of using deep learning techniques in a range of medical image analysis applications. We highlight, in particular, the most recent developments and contributions of cutting-edge unstructured and semi-supervised deep learning for the analysis of medical images, which are compiled based on several application situations, such as image registration, categorization, separation, and detection.

(Karimi, D., 2020) [23] Generously labeled datasets are necessary for the directed development of deep learning models. Acquiring such datasets for analysis of medical image applications is becoming more and more popular. Nevertheless, not enough emphasis has been placed on the effects of label noise. Label noise has been proven in recent research to have a major effect on deep learning model performance in a variety of computer vision and machine learning algorithms.

This is especially problematic for healthcare applications since they often have short datasets, labeling needs domain knowledge and suffers from significant variability between and among observers, and incorrect predictions might have an effect on choices that have a direct bearing on human health. To handle noise related to labels in deep learning algorithms, we first evaluate the state-of-the-art in this work.

(Chen, M., 2017) [24] Computed Tomography (CT) is a commonly used tool to help diagnose illness these days. Particularly, Artificial Intelligence (AI)-based Computer Aided Diagnosis (CAD) has shown its significance in intelligent healthcare in recent times. However, because of security and safety concerns, it is very difficult to build a sufficient labeled database for CT analysis help. This research suggests an automatic convolutional auto-encoder using the deep learning framework to enable unsupervised image feature learning for lung nodules using unlabelled data. This system only requires a limited quantity of labeled data for effective feature learning. Extensive tests show the superiority of the suggested system over other solutions, which successfully addresses the labor-intensive issue inherent in artificial picture tagging. Furthermore, it confirms that lung nodule image similarity can be measured using the suggested convolutional auto-encoder technique. In particular, the characteristics gleaned by unsupervised learning may be used in other relevant contexts.

(Latif, J., 2019) [25] Dynamic medical imaging research is seeing tremendous growth in deep learning, machine learning, and other methods. At the moment, significant efforts are being made to improve medical imaging applications by applying these algorithms to identify flaws in illness diagnosis systems that might lead to very unclear medical interventions. In medical imaging, algorithms using deep learning and machine learning play a significant role in predicting early illness signs.

Deep learning methods have quickly produced a unique approach for analyzing medical pictures, particularly in convolutional networks. Displaying the predictions uses supervised or unsupervised methods using a certain standard dataset. We review medical imaging principles such as object identification, pattern recognition, reasoning, and picture categorization. Through the extraction of relevant patterns particular to a certain condition in medical imaging, they are utilized to increase accuracy. These methods also support the process of making decisions. The main goal of this survey is to showcase the machine learning and deep neural network methodologies used for medical picture analysis.

METHOD

There are three sections here. The medical datasets used in this study are covered in the first section. Preparatory processing, the process of segmentation and feature extraction are steps in the data analysis of the medical data set that are covered in the second section [26]. The diagnostic and assessment step, covered in the third component, entails using methods for the classification of the chosen medical datasets and assessing the results of these algorithms.

Medical Datasets

Two sets of healthcare datasets were employed in this work. The first group had pictures from chest X-rays, while the second group contained dermoscopy images for skin cancer melanoma. 30% of these datasets were set aside for testing, while the remaining 70% were used for training.

The Dataset for Chest X-rays

Kaggle provided the chest X-ray photos of the typical and unusual lung instances. For the proposed methodology, a dataset comprising 612 successful images was used; of the 612 photographs of lungs that were approved in this work, [27], 288 images showed lungs in good condition, and 324 images showed lungs affected by various lung diseases, including COVID-19, respiratory illnesses, pulmonary em fibrosis, lung transparency, and bacterial and viral diseases. JPG format images were taken in different resolution sizes, however all sizes were standardized to 256 × 256 pixels. Normal and abnormal lung pictures from the chest X-ray database are displayed in Figure 2.

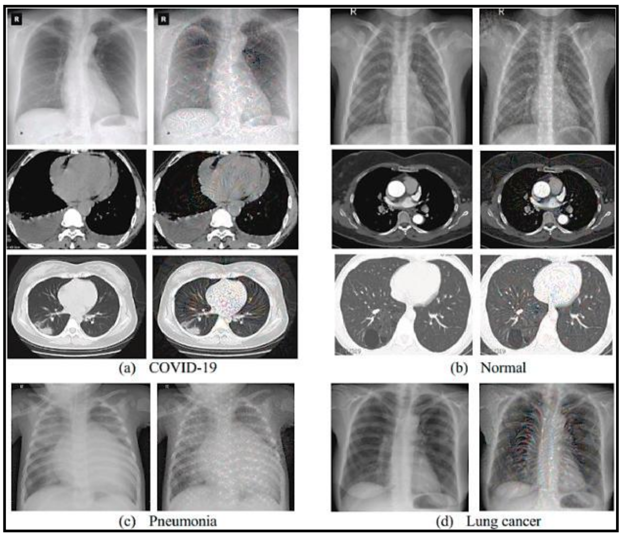

Fig. 1 Chest X-ray dataset samples include: (a) COVID-19; (b) normal lung pictures; (c) pneumonia; and (d) lung images.

The Skin Cancer and Melanoma Dermoscopy Dataset

The Dermatology Online Atlas and The Lloyd Dermatologist and Laser Centre provided the dermoscopy samples of the metastatic skin cancer. The suggested methodology was assessed on a dataset of 300 images. Of the 300 images of skin cancer from melanoma used in this work, 145 showed benign conditions and 155 showed malignant ones, including various forms of malignant melanoma such as nodule, lentigo, [28], superficial spreading, and accrual melanoma that is malignant. Similar to the last instance, the photographs were taken in the JPG format and their sizes were standardized to 256 × 256 pixels in order to accurately extract characteristics that differentiate between images of malignant and benign melanoma skin cancer. Benign and malignant photos from the melanoma from skin cancer dermoscopy, especially databases are shown in Figure 3.

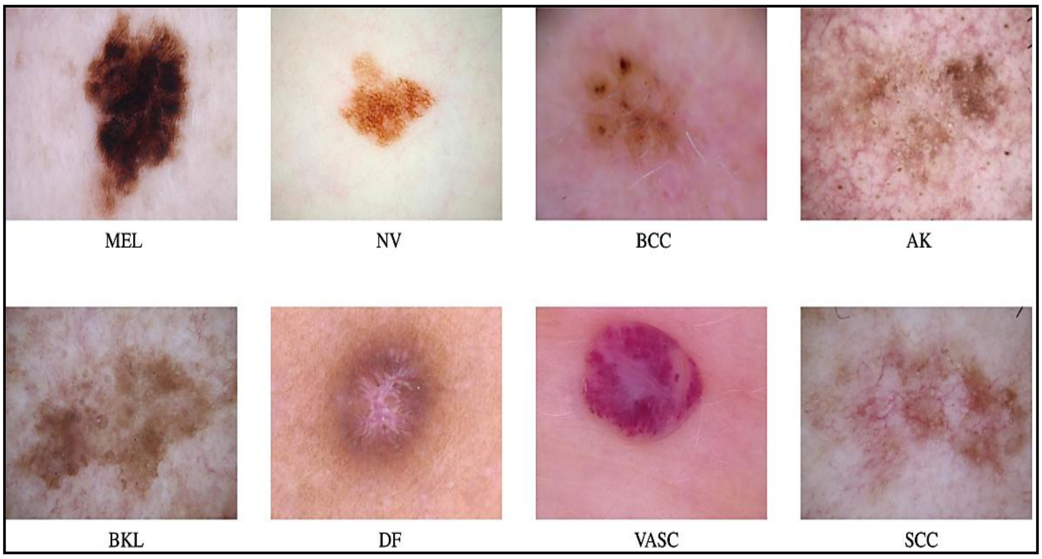

Fig. 2 Skin cancer samples from melanoma using dermoscopy dataset.

RESULT AND DISCUSSION

This section presents a comparison of the findings and the results of all the techniques used in the categorization that were developed using Mat lab 2021.

Table 1 presents the results of several classification techniques together with metrics for performance for all algorithms for machine learning and deep learning algorithms CNN applied to the skin cancer with melanoma dermoscopy database or chest X-ray dataset [28].

Table 1 Classification results for the lung disease dataset

Algorithm	Acc%	Sn%	Sp%	Pr	Recall	F-measure	AUC
ANN	94.8	98.7	0.988	0.846	0.416	0.489	0.149
SVM	87.9	85.9	0.749	0.896	0.216	0.490	0.549
DT	97.8	98.8	0.589	0.476	0.549	0.549	0.219
NB	87.6	78.9	0.586	0.496	0.216	0.496	0.489
LR	97.8	87.9	0.479	0.589	0.496	0.596	0.618
RF	86.4	74.8	0.896	0.151	0.296	0.549	0.249
RS	84.8	98.8	0.479	0.264	0.489	0.219	0.216
Fuzzy logic	79.8	97.8	0.146	0.894	0.549	0.496	0.249
CNN	79.5	96.8	0.418	0.196	0.796	0.216	0.249

The test accuracy comparison of the algorithms for categorization used to the two medical picture datasets utilised in our study is shown in Table 2.

Table 2 Comparison of the two medical datasets categorization systems' accuracy

Algorithm	Accuracy in the first Database (chest X-ray)	Accuracy in the second Database (melanoma skin cancer Dermoscopy)
ANN	98.6%	94.4%
SVM	97.5%	97.8%
DT	96.4%	96.7%
DB	74.5%	95.8%
LR	96.4%	96.8%
RF	78.8%	94.1%
RS	97.8%	94.2%
Fuzzy logic	96.4%	93.5%
CNN	97.8%	97.8%

A fresh set of 100 photos from the medical dataset included in this study were utilized for validation to assess the correctness of the final optimized model [29]. The verification of the accuracy of the techniques for classification applied to the two medical picture datasets used in our study is shown in Table 3. We see that the validation findings closely match the test outcomes of the categorizing methods used with the two sets of clinical imaging data [30].

Table 3 The outcomes of the classification algorithms' accuracy validation for the two medical datasets

Algorithm	Accuracy in the first Database (chest X-ray)	Accuracy in the second Database (melanoma skin cancer Dermoscopy)
ANN	87.9%	92.5%
SVM	94.8%	84.1%
DT	96.1%	74.8%
DB	97.8%	94.1%
LR	96.8%	93.5%
RF	94.8%	91.4%
RS	94.8%	96.2%
Fuzzy logic	89.7%	92.4%
CNN	94.8%	97.8%

CONCLUSION

The skin cancers with melanoma dermoscopy and chest X-ray datasets were used in this study for categorization. 30% of the data has been employed for testing, while 70% were used for training. The primary analytic procedures were used to examine the data, and the medical data pictures underwent pre-processing to reduce noise and improve contrast. A few filters were implemented to enhance the pictures. The median filter was used to pre-process the chest X-ray images, and the histogram's equalisation enhancement was employed to optimize the brightness and eliminate noise. Using the technique suggested in the paper, hair was extracted from the skin cancer diagnosed with melanoma photographs to enhance them and make them ready for the subsequent step of analysis, which included separating the noteworthy item from the background of the pictures.

The recommended segmentation methods were used to use Otsu thresholding technique with the banalization and negation procedures to separate the area of damage from skin cancer pictures and to separate the lung from chest X-ray images using thresholding technique and morphological processes.

The suggested segmentation algorithms performed a great job of removing the item from the image and extracting features, so the next step was able to begin. Here, the best techniques were used to extract features from the photographs, such as colours, appearance, and certain geometry characteristics, and to go on to the most crucial step, which is the classification. Relevant features extracted from the images included texture and shape.

At this point, in in addition to CNN for deep learning, we apply a set of the most significant and well-known machine learning-based classification techniques, such as ANN, SVM, KNN, DT, NB, LR, RF, RS, and fuzzy logic in order to determine the effectiveness of these algorithms and the precision of their classification.

All of these findings were made achievable by training the chosen databases and receiving results, whereby the majority of the techniques shown produced outstanding results and were successful in recognizing lung disorders and skin cancer caused by melanoma.

Accuracy, particularity, sensitivity, recall, precision, and the F-measure were used to assess the model. The findings' analysis, however, suggests that there is room for improving the performance of certain approaches by using one another, maybe hybrid or superior methods.

This will speed up performances and cut down on the time, expense, and effort associated with illness diagnosis. The algorithm's accuracy and performance are dependent on the type of medical dataset, the quantity of data, the type of infection, and the effectiveness of the methods used during the preliminary processing, the process of segmentation and feature-extraction stages, according to a comparison of the application of diagnostic and monitoring methods to the two sets of medical picture data sets.

FUTURE WORKS

We plan to develop a hybrid classifier in the future by combining two or more classification techniques to create a new classification model architecture.

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