MEDICAL IMAGING USING MACHINE LEARNING, COMPUTER VISION AND APPLICATIONS

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ABSTRACT

Machine learning (ML), which has become a formidable tool in the fields of medical imaging (MI) and computer vision (CV), may now be used to study large and complex medical datasets. This has made it possible to significantly improve illness detection, segmentation, diagnosis, and prognosis, among other things. The quantity and quality of medical data, interpretability, legal and ethical issues, and interactions with clinical procedures are only a few of the issues that still need to be solved. Collaboration between researchers, physicians, governmental policy decision-makers, and industry members will be necessary for the successful use of ML in MI and CV. ML has the power to change MI and CV despite the difficulties, resulting in better patient outcomes, diagnoses, and more effective medical care.

KEYWORDS: *Medical images, Machine Intelligence, Cross Validation, deep learning, deep convolution neural networks artificial intelligence, machine learning.*

1. INTRODUCTION

Computer systems can get better by learning from their mistakes and analysing data with the aid of machine learning (ML), a branch of artificial intelligence (AI). Machine intelligence (MI) and Cross Validation (CV) are two areas where ML has recently shown tremendous expansion.

Medical imaging data from X-rays, MRIs, and CT scans can be analyzed with ML algorithms in MI to find anomalies and track the progression of diseases. Using ML algorithms to help identify patterns and trends in MI data can help healthcare professionals make more accurate diagnoses and better treatment decisions [1].

In CV, ML algorithms can be applied to analyze images and videos in order to distinguish faces, identify objects, and detect anomalies. By examining massive databases of images and videos for patterns and trends, ML algorithms can be used to improve the accuracy of image identification and classification.

There are many ML techniques that can be applied to MI and CV, such as reinforcement learning, supervised learning, and unsupervised learning. On a labelled dataset with known input data and desired output, an ML algorithm is taught via supervised learning. Unsupervised learning is used to train a machine learning algorithm on an unlabeled dataset where the input data is known but the desired output is not. Reinforcement learning is used to educate machine learning algorithms to base decisions on input from their environment [2].

The identification and management of diseases could be completely changed by the application of machine learning (ML) in MI and CV.

In MI and CV, ML is being used more and more to enhance illness diagnosis, therapy, and monitoring. ML algorithms may now be trained to recognize patterns in medical images like X-rays, CT scans, MRIs, and ultrasounds that are difficult for human professionals to identify due to the growth of high-performance computing and the accessibility of vast data sets.

The algorithms for machine learning in medical imaging need a lot of data to be trained and tested. These details may be found in hospital or radiology department MI archives. The conversion of MI data into a format that ML algorithms can use requires specialized software because it is typically in a complex format, such as DICOM [3].

ML algorithms are referred to as deep learning, a kind of ML that uses neural networks with several layers. Deep learning algorithms are capable of accurately predicting outcomes from complex patterns found in medical imagery [4].

Some of the challenges associated with using ML in MI and CV include the requirement for large datasets with annotations, the interpretability of ML algorithms, and concerns about data security and privacy. Overall, ML has the power to transform MI and CV while improving patient outcomes.

2. LITERATURE REVIEW

In the past, researchers have created a number of techniques for extracting both high-level and low-level information from images. Corner points, edges, color intensity, and scale-invariant features like SURF (Speeded up Robust Features) and SIFT (Scale Invariant Feature Transform) [32, 33] are examples of typical features. Because SIFT and SURF are invariant to image scale, rotation, posture, and lighting, which were regarded as major issues in CV and medical imaging, these features have drawn significant interest from the research community. Then, ML models are trained to carry out a particular supervised classification job using these attributes. With the help of machine learning (ML), computers may learn from past observations without the need for explicit programming or the creation of heuristics to take into account the virtually limitless number of possible combinations of features in these observations.

There is a broad variety of ML algorithms [34], and the kind, amount, and complexity of the data and the task are frequently important considerations when selecting an approach. Support vector machines (SVM) [35], ensemble-based techniques like random forests (RF)[21], artificial neural networks (ANN)[36], and others are typical machine learning (ML) techniques. This conventional method was the most often used method of handling CV tasks, such as classification, object recognition, and object tracking, before the usage of deep learning (DL) and deep convolution neural networks (CNN) [37] became popular in 2012. The performance of the selected ML model would largely depend on the calibre of the extracted image features, which is a significant drawback of such a method.

Since 2012 [37], great progress has been made in the CV area thanks to the developments in deep learning and CNN research and development. DL-based techniques are also becoming more and more common. They are currently regarded as the most popular and best-performing algorithms for handling several CV jobs. Traditional methods that use hand-crafted features and DL-based methods differ primarily in that the latter are able to learn the features (underlying representation) of the input images in an end-to-end manner without the need for feature extraction or engineering, as demonstrated by Gumbs et al.[42]. The performance of DL models has greatly increased not only in CV but also in a variety of other fields, including gaming and AI [38], natural language processing [39], health [40], cyber security [41], and others.

3. MEDICAL IMAGING USING MACHINE LEARNING

MI makes use of a branch of machine learning known as "deep learning," which makes use of multilayer neural networks. Deep learning algorithms have the capacity to recognise intricate patterns in body image images and generate precise predictions [10, 11]. Figure 1.1's condensed flowchart illustrates how machine learning functions in MI.

3.1 Raw Data: This set of medical imaging data serves as the foundation for the machine learning process. Information from many imaging methods, including as X-rays, CT scans, MRIs, and ultrasounds, may be included.

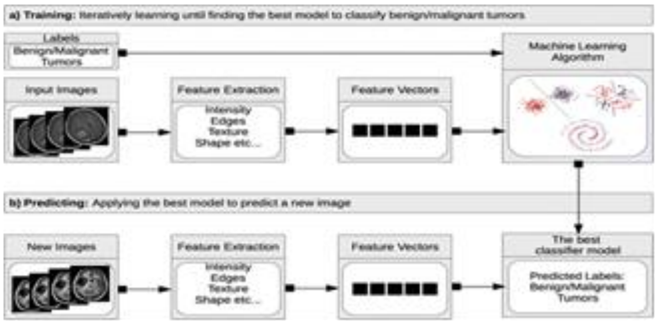

Figure1. Medical imaging with machine learning

The following list of stages includes details:

3.2. Data pre-processing: At this stage, the unclean, unformatted medical imaging data is cleaned up and transformed into a form that machine learning algorithms can understand. This may involve performing procedures like removing noise and artifacts, enhancing the image quality, and segmenting areas of interest.

3.3. Feature Extraction: Features that are relevant to the present MI problem are produced and selected in this step. To extract characteristics, many aspects of the images, such as texture, shape, and intensity, can be utilised. The photographs can also have features automatically extracted from them utilising deep learning-based feature extraction techniques.

3.4. Model Training/Evaluation: Using the features and data that have already been analysed in step four, a machine learning algorithm is taught. The model's performance is then evaluated. In this procedure, measures like sensitivity, specificity, accuracy, and precision are determined as well as the area under the receiver operating characteristic curve (AUC-ROC).

3.5. Model Deployment: A machine learning model can be applied in a clinical setting after being trained and evaluated. The model may require integration into MI software, the creation of an API, or the design of a user interface.

Here are a few examples of machine learning models that have been used in MI [12] specifically:

• CNNs for image segmentation, abnormality or lesion detection, and image classification based on the kind or severity of the disease.

• Generative Adversarial Networks (GANs), which may synthesis medical images to augment small datasets or produce realistic training images.

4. MACHINE LEARNING MODELS FOR MEDICAL IMAGING AND COMPUTER VISION

Numerous ML techniques are commonly used in medical imaging. Some of the most well-liked ones are listed below [10].

4.1 Convolution neural networks (CNNs)

CNN are a subset of deep learning algorithms that are particularly adept at tasks like segmentation, classification, and abnormality detection in medical pictures. They have shown a lot of promise in this regard.

4.2 Support vector machines (SVMs)

SVMs are a type of supervised learning method that can be applied to classification tasks. They are commonly used in binary classification tasks, including separating healthy from unhealthy tissue in body photos.

4.3 Random forests

To improve prediction accuracy, this ensemble learning technique combines different decision trees. They are frequently used for image segmentation and classification tasks in medical image analysis.

4.4 K-nearest Neighbors (KNN)

For categorization tasks, KNN is a straightforward but powerful machine learning algorithm. It is frequently employed in medical imaging to do image classification tasks like categorizing various tissue types in an image.

4.5 Deep belief networks (DBNs)

Deep learning uses DBNs, an unsupervised learning method. They perform effectively during image denoising and reconstruction processes in medical imaging.

These are only a handful of instances of how machine learning methods are frequently applied in medical imaging. The algorithm chosen depends on the particular issue being addressed and the properties of the data being examined [13].

5. Role of Machine Learning Algorithms in Medical Imaging and Computer Vision

5.1 MI and computer vision are greatly aided by machine learning (ML) methods, which automate and improve the processing and interpretation of visual input. Here are a few specific examples of how ML algorithms have been used in different fields [1, 3].

5.2 Medical image analysis using machine learning (ML) algorithms can spot patterns and anomalies that may be challenging for human experts to spot in real-world situations. As a result, diagnoses are made more swiftly and precisely, and treatment strategies are better tailored to the patient.

5.3 In order to discover early signs of diseases like cancer, machine learning (ML) algorithms can assess vast amounts of medical imaging. This enables earlier interventions and improved patient outcomes.

5.4 Image segmentation and registration of machine learning (ML) algorithms can help identify areas of interest and align several images for more accurate analysis and diagnosis by segmenting and registering medical images.

5.5 Computer-aided detection and diagnosis ML algorithms can aid radiologists and other medical professionals in the identification and diagnosis of diseases, reducing errors and boosting accuracy.

5.6 Surgical planning and augmented reality: Machine learning algorithms can generate 3D models from medical images, allowing for more accurate surgical planning and the use of augmented reality in medical procedures.

5.7 The use of computer vision in healthcare includes the identification of patients using facial recognition, surgical navigation using gesture analysis, and emotional support for patients using emotion recognition. ML algorithms can be used in these applications.

5.8 The use of ML algorithms in MI and computer vision is still in its infancy, and challenges still need to be overcome, such as the need for enormous amounts of high-quality training data, the potential for bias in the algorithms, and the demand for interpretability and transparency. However, with further research and development, ML algorithms have the potential to change the fields of computer vision and MI, leading to better patient outcomes and more efficient healthcare delivery [16].

6. MEDICAL IMAGING APPLICATIONS

6.1 Diagnostic imaging and radiology

Radiology and diagnostic imaging use a wide range of medical imaging techniques to detect and monitor a multitude of disorders. The manner that medical image analysis and viewing are done has altered thanks to deep learning and artificial intelligence. Here [18] are some significant radiology and diagnostic imaging applications.

6.1.1 Image interpretation: The application of deep learning and AI algorithms by radiologists can lead to improved accuracy and productivity. For instance, machine learning algorithms are able to quickly identify and focus on anomalies in CT scans, MRI pictures, and X-rays [21]. This can increase the early detection of diseases and speed up the diagnosing process.

6.1.2 Computer-Aided Detection/Diagnosis: CAD systems analyze medical pictures using AI and deep learning models, highlighting probable problems for radiologists to further examine. These devices can alert radiologists to questionable areas, such as lumps or tumours, and help them make more precise diagnosis [19].

6.1.3 Reconstruction and enhancement of images: Image quality and low-dose imaging have been enhanced using deep learning algorithms. Large data sets are used by AI systems to reconstruct high-quality images from scans of lower resolution. The acquired photos, however, are noisy and lacking. A range of picture reconstruction and enhancement techniques are used to address these problems. Reconstruction using the Fourier transform, parallel imaging, compressed sensing, image enhancement filters, and machine learning-based algorithms like CNN are a few typical ways [21].

6.2 Pathology

The study and examination of images made from tissue samples or specimens is known as pathology and is a subfield of medical imaging. Microscopes are used by pathologists to analyse tissue samples. Pathologists are crucial in the diagnosis of sickness, finding anomalies, and determining the course of treatment. While physical sample examination is still necessary, deep learning and AI systems have opened up new possibilities. Medical imaging and pathology have a close relationship.

6.2.1 AI-Assisted Pathology: Artificial intelligence (AI) is the ability of a computer system to learn and solve problems in the same manner as a human. AI should be able to do all tasks that need human intelligence, including visual perception, decision-making, and communication. AI-based computational pathology, a topic that is still relatively young, has shown a lot of promise in terms of increasing the accuracy and accessibility of high-quality medical care for patients across a wide range of disciplines. Because of the enormous amount of data produced during the patient care lifecycle, using AI technology can enhance the pathologic diagnosis, categorization, prediction, and prognosis of diseases [6].

6.2.2 Image analysis and quantification: There are several qualities to medical imagery. For enhanced image quality, these qualities need to be measured and examined. CNN has developed as a crucial imaging tool for healthcare [22].

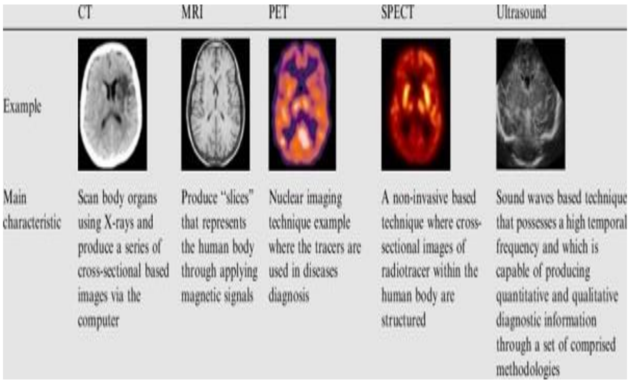

Figure 2. Various Ways of Medical Imaging [7]

6.3 Cardiology

6.3.1 Wearable technology: These gadgets can keep an eye on things like heart rate, activity level, sleep patterns, and even abnormal heart rhythms.

They offer valuable information that can be used to monitor heart health and spot early warning symptoms. Two popular examples of wearable electronics are smart watches and fitness trackers [12].

6.3.2 Cardiac Imaging: Thanks to improvements in cardiac imaging technologies like echocardiography, cardiac magnetic resonance imaging (MRI), and computed tomography (CT), it is now possible to observe the structure and function of the heart. These techniques assist in the diagnosis of heart disease, guide treatment decisions, and assess the efficacy of interventions [28]

6.4 Neuroimaging

6.4.1 FMRI: The widely used neuroimaging technique known as fMRI has the ability to assess brain activity by monitoring changes in blood oxygenation levels. Our understanding of how the brain functions and is connected has changed. The use of fMRI in cognitive neuroscience research makes it possible to identify brain regions that are involved in a variety of cognitive processes, including language processing, memory, attention, and emotion [16].

6.4.2 Diffusion Tensor Imaging (DTI): Researchers are currently able to learn more about how the brain develops, how unusual connections in neurological problems affect these diseases, and how these disorders subsequently evolve with the help of diffusion tensor imaging. The DTI MRI techniques have particular competence in evaluating water particle diffusion in brain cells. The connections between the brain's structural components can be seen by identifying white matter pathways [17].

6.3.3 Positron Emission Tomography, or PET: In this method of monitoring, radioactive tracers are used to monitor the metabolic and biochemical activities of the brain [18].

7. Conclusion and Future Perspective

ML has shown exceptional potential in MI and CV due to its ability to analyse large, complex medical datasets and to significantly improve the detection, segmentation, diagnosis, and prognosis of disorders. A few of the problems that need to be handled involve the quantity and quality of medical data, interpretability, legality, ethics, and connection with clinical workflows.

Overcoming these challenges will require continued collaboration between researchers, physicians, policymakers, and industry stakeholders in the future directions for ML in MI and CV. Building more trustworthy and intelligible ML models is important, in addition to addressing issues with bias and generalizability.

A growing trend is to combine ML with other technologies like virtual reality and augmented reality to create immersive and interactive MI and CV apps. This could open the door to entirely new systems of medical education, teaching, and collaboration, which could result in even more dramatic changes to MI and CV.

In general, ML has the potential to change MI and CV, leading to improved patient outcomes, better diagnosis, and more efficient medical treatment. As research in this area progresses, it is important to address the challenges and opportunities presented by this powerful technology.

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