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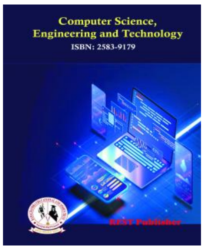

Agile Biomedical Image Processing in Medical Diagnosis Using Deep Learning Method

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Abstract. Biomedical image processing is essential for accurate and efficient medical diagnosis. This research presents an agile Deep Learning (DL)-based approach to enhance diagnostic precision and speed. The methodology employs Convolutional Neural Networks (CNNs) and other DL models for automated feature extraction, classification, and anomaly detection. The agile framework ensures adaptability to various imaging modalities, supporting real-time analysis. The study evaluates the approach using medical image datasets, demonstrating improved accuracy and reduced processing time. Results highlight its effectiveness in detecting abnormalities with high precision. Compared to traditional methods, the proposed approach enhances diagnostic reliability. The agile integration of DL optimizes image processing workflows. This framework supports rapid updates and adaptation to evolving medical imaging requirements. Scalability and efficiency make it suitable for diverse clinical applications. The study underscores deep learning's role in modern medical diagnostics.

Keywords: Deep Learning, Convolutional Neural Networks, Biomedical imaging, Generative Adversarial Networks.

1. INTRODUCTION

The prompt and precise detection of medical disorders is the most crucial element for patients as well as medical professionals in this model healthcare scenario. This is an important indicator of patient happiness as well as the effectiveness of the care recipient's health care. However, there are still delays in diagnosis even with the tremendous developments in medical imaging technologies. Research conducted by the Society to Improve Diagnosis in Medicine (SIDM) found that diagnostic delays impact an estimated 12 million Americans per year, which also accounts for 10% of all patient fatalities in the US. In Kerala, it was discovered that the main cause of patients' longer infectivity periods and worsening illness severity was delayed diagnosis of Tuberculosis (TB). It is revealed that unexpected clinical presentations, testing restrictions, and a refusal to cooperate with other specialists were the main causes of diagnosis delays [1].

Biomedical image processing is an interdisciplinary field built upon various domains, including physics, electronic engineering, computer science, mathematics, physiology, and medicine. Various imaging techniques have been developed to facilitate the examination of the human body. These include computed tomography utilizing X-rays, magnetic resonance imaging, ultrasound technology, radiation therapy involving radioactive substances for both positron and single-photon emission tomography, elastography, functional near-infrared spectroscopy, photoacoustic imaging-assisted endoscopy, thermography, and numerous other advanced methods. Data obtained from bioelectric sensors utilizing high-density systems to capture two-dimensional surface signals, such as those in electroencephalography or electromyography, can be analyzed through image processing techniques. There are more and more significant uses for biomedical image processing, such as segmenting images of organs to examine their interior structure and aid in illness diagnosis or treatment planning [2].

Processing, interpreting, and analysing medical images are all part of the study area known as medical image analysis. Due to their increasing use in recent years to enhance the diagnosis, treatment, and monitoring of numerous medical conditions, DL algorithms have brought about a substantial change in the field of medical image analysis [3]. DL is a branch of Machine Learning (ML) that focusses on training methods to derive information from massive data sets. In the context of the analysis of medical images, algorithms based on DL can automatically detect and classify abnormalities in ultrasound, MRI, CT, and X-ray pictures, among other medical imaging [4]. Large datasets of annotated medical images—each image with a label indicating the related medical disease or abnormality—can be used to train these algorithms. After being taught, the algorithm can evaluate fresh medical photos and give medical practitioners diagnostic information. Studies showing excellent levels of accuracy in identifying and diagnosing a variety of medical diseases [5] demonstrate the promising results of using DL algorithms to medical picture analysis. As a result, numerous open-source and commercial software applications that use DL algorithms for medical picture interpretation have been developed [6]. In general, the application of DL algorithms to medical image processing holds promise for significantly improving healthcare outcomes and revolutionising the use of medical imaging for both screening and treatment.

"DL" is a branch of ML that uses neural networks with multiple layers to find and extract intricate patterns from big datasets [7]. Natural language processing (NLP), image processing, and recognition of speech are just a few of the areas it has transformed. One of the key advantages of deep learning is its capacity for automatically obtaining features from raw data, eliminating the necessity for human feature engineering. As a result, it works especially well in domains with large, complex datasets, where traditional ML methods would struggle to spot the essential patterns. DL has also enabled significant improvements in other areas, including speech and image recognition, NLP, and the development of autonomous vehicle capabilities [8]. For instance, DL has enabled the development of highly precise computer vision systems that are capable of precisely identifying objects in images. Similar to this, DL has significantly improved NLP, resulting in models that can understand and produce language that is similar to human expression [9]. DL has opened up new ways to solve difficult problems and has the potential to transform a variety of industries, such as health care, finance, and transport.

ML algorithms are widely used for accurate and effective segmentation jobs in the field of medical image analysis using DL techniques. Medical images contain symmetrical characteristics and spatial dependencies that DL techniques, specifically CNNs and Recurrent Neural Networks (RNNs), have demonstrated remarkable proficiency in gathering and applying. By utilising their innate symmetrical patterns, these algorithms make it possible to analyse medical images of symmetrical structures, including organs or limbs. The application of DL mechanisms in the analysis of medical images includes a number of useful techniques, including CNN/RNN combinations, hybrid algorithms, and Generative Adversarial Networks (GANs). The purpose of this work is to present a thorough summary of the uses of image analysis based on deep symmetry in the medical field by conducting a detailed investigation of these approaches.

2. LITERATURE REVIEW

Tao et al., have seen a surge in computer vision research in the field of deep learning-based picture fusion algorithms. This research examines these strategies from five distinct perspectives. First, the theory and benefits of picture fusion methods based on DL are explored. Second, the image fusion techniques can be summed up in two key ways: Due to the different functions that DL plays in the feature processing stage, throughout its entirety and non-end-to-end image merging algorithms are divided into two categories: DL based decision mapping and feature extraction. Three categories can be used to group end-to-end picture merging techniques. These include encoder-decoder, generative adversarial, and convolution neural networks. The approach and data set for applying deep learning-image fusion methods in the medical imaging domain are best described by two words, which comes in third. Fifth, the main challenges in medical picture fusion are examined in two sections: data sets and fusion techniques. Fourth, the 14 components of the assessment criteria that are frequently employed in the field are classified. Future development trends are also anticipated. In order to provide future research on multimodal medical pictures a direction, this work provides a comprehensive evaluation of deep learning-driven image fusion techniques [10]. Altini et al., have suggested a CAD system for glomerulus identification and evaluation from kidney tissue slides. They use CNN architectures specifically designed for the semantic segmentation task in their deep learning-based methodology. Expert pathologists also expressed optimism about the outcomes produced. Aperio ImageScope's XML interface also makes it simple to incorporate the suggested method into the current pathologists' workflow [11,12].

Tajbakhsh et al., have examined the minimum amount of data needed to train a CNN for clinical DL or the potential of having limited annotations, despite the fact that a ML algorithm's success is dependent on the quantity of accessible data. This Special Issue presents an original effort. To train a U-Net that correctly separates the prostate on T2-weighted MRI images, the research investigates the smallest number of patients needed. Patient numbers ranging from 8 to 320 were used to train a U-Net, and its effectiveness was evaluated. Between training sessions of 8 and 120 patients, the Dice score grew dramatically; however, after 160 cases, it stalled with minimal advancement. According to this work, other organs may also be successfully segmented using modest dataset sets [13,14].

Kumari et al., have went into further detail, stating that the field of medical image analysis has greatly advanced due to the quick development of DL. The absence of sizable, well-annotated datasets remains a major barrier to the advancement of DL models for medical image processing, notwithstanding these achievements. In recent years, there has been increased focus on developing data-efficient DL methods to get around this problem. In this paper, a comprehensive assessment of data-efficient DL methods for medical picture analysis is provided. This is accomplished by classifying the procedures according to the degree of supervision they require, comprising groups that need no supervision, exact supervision, limited monitoring, inaccurate oversight, and inadequate oversight [15].

According to Yi et al., robustness is essential in the medical field to guarantee that regular, correct diagnoses are made despite variations in information about patients, imaging procedures, or other elements that could compromise the provided data's quality. The ability to reliably produce accurate diagnoses under a variety of circumstances is a crucial characteristic of DL models utilised by health care systems. These models must also be able to handle a broad range of inputs, including diverse kinds of clinical information or medical images. A number of medical diseases can be accurately identified and diagnosed by medical systems that use DL models. However, these models are vulnerable to adversarial attacks, where malicious entities alter input data to deceive the model, thus leading to false diagnoses [16,17].

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Ismail et al., have published a CNN-based model to analyse routine health indicators in an Internet of Medical Things (IoMT) setting. In order to predict the possibility of health problems, the model used CNN-based algorithms to obtain features from various health-related sources, including the temperature of the body, pulse rate, and blood pressure. Five groups of health data can be distinguished by the proposed model: normal, pre-hypertension, pre-diabetes, hypertension and diabetes. The model was trained and evaluated by the authors using a real-world dataset that included health data from 50 people. In terms of both prediction accuracy and computing complexity, the results showed that the suggested model outperformed current ML models and demonstrated an impressive degree of accuracy. In order to prevent health problems and improve patient outcomes, the authors stated their confidence that the suggested approach might help enhance health monitoring systems by providing real-time monitoring and tailored interventions [18].

3. RESEARCH METHODOLOGY

Biomedical image processing plays a crucial role in accurate medical diagnosis, and this study adopts an agile deep learning-based approach to enhance its efficiency. Medical image datasets, including MRI, CT scans, and X-rays, are utilized, with preprocessing techniques such as noise reduction, contrast enhancement, and normalization applied to improve input quality. Image augmentation methods, including rotation, flipping, and scaling, enhance model generalization. CNNs and other DL models are implemented for automated feature extraction and classification, incorporating transfer learning and fine-tuning to optimize performance. An agile framework ensures adaptability to various imaging modalities through iterative updates and real-time feedback, facilitating continuous improvements. The proposed approach is evaluated using benchmark medical image datasets, with key performance metrics such as accuracy, sensitivity, specificity, and processing time analysed. Additionally, the framework is tested for scalability across different imaging applications, ensuring seamless integration into real-time diagnostic workflows. This methodology enables the development of a robust, adaptive, and efficient DL-based biomedical image processing system for enhanced medical diagnosis.

Image analysis and its function in medical healthcare: Medical healthcare has undergone a revolution on account of DL algorithms for image analysis, which enable sophisticated and automated interpretation of medical pictures. Remarkable performance has been demonstrated by DL techniques, such as CNNs, in tasks such as image categorisation, feature extraction, and classification. DL algorithms can identify complex patterns and correlations in medical images by utilising vast volumes of annotated data. This allows for precise disease and abnormality detection, localisation, and diagnosis. Enhanced patient outcomes, individualised treatment planning, and more effective healthcare processes are all made possible by DL-based image analysis, which enables quicker and more accurate assessment of medical images. Additionally, by analysing massive image databases, these algorithms can help radiologists make decisions, aid in early disease identification, and advance research in medicine. All things considered; by offering strong tools for picture interpretation, boosting the skills of medical experts, and improving patient care, deep learning-based image evaluation is revolutionising medical healthcare [19,20].

Application of medical image analysis: DL techniques for medical image processing have found several uses in the medical field. Image segmentation, identification of objects, disease categorisation, and image reconstruction are among the tasks for which DL methods, particularly CNNs, have been extensively used. These methods can help identify and diagnose disorders including tumours, lesions, anatomical anomalies, and pathological alterations in medical picture analysis. Additionally, they can be used to assess prognosis, therapy response, and disease progression. Effective and precise interpretation of medical images is made possible by the automatic extraction of significant characteristics by DL models. In healthcare settings, the use of this technology has the potential to improve medical decision-making, enhance the treatment of patients, and maximise the allocation of resources. Additionally, data enhancement, image authorisation, and multimodal integration can be accomplished with DL algorithms, enabling a thorough and cohesive examination of medical images acquired from several modalities. Medical image analysis is making great strides thanks to ongoing developments in DL algorithms, which are creating new opportunities for cutting-edge healthcare solutions, personalised treatment plans, and precise medicine.

Data Collection and Preprocessing: Medical image datasets, including MRI, CT scans, and X-ray images, are utilized to develop and evaluate the proposed deep learning-based biomedical image processing approach. These datasets are sourced from publicly available repositories and clinical archives to ensure diversity in imaging modalities and pathological conditions. Preprocessing methods including normalisation, contrast improvement, and noise mitigation are used to improve the input data's quality and consistency. Noise reduction filters minimize artifacts and improve image clarity, while contrast enhancement techniques optimize the visibility of critical anatomical and pathological features. Normalization ensures uniform intensity distribution across images, facilitating effective model training and improving diagnostic accuracy. Additionally, image augmentation techniques, including rotation, flipping, scaling, and cropping, are utilized to increase dataset variability and improve model generalization. These preprocessing steps are essential for optimizing the DL framework, ensuring robust and efficient medical diagnosis across various imaging scenarios. Table 1 shows the datasets for disease detection and diagnosis.

TABLE 1. Medical Imaging Datasets for Disease Detection and Diagnosis

Dataset Name	**Imaging Modality**	**Application**	**Description**
ChestX-ray14	X-ray	Lung disease detection	Large-scale dataset for pneumonia, tuberculosis, and other lung conditions.
LIDC-IDRI	CT	Lung nodule detection	Annotated thoracic CT scans for lung cancer screening.
BraTS	MRI	Brain tumor segmentation	MRI scans for detecting and segmenting brain tumors.
ISIC	Dermoscopy	Skin lesion classification	Dataset for melanoma detection and skin disease classification.
MIMIC-CXR	X-ray	Radiology report generation	De-identified chest X-ray images with corresponding medical reports.

Agile-Driven DL model implementation for biomedical image processing: CNNs to enhance disease diagnosis and classification. While CNNs have been effective in medical imaging, they face challenges such as the high cost and complexity of data collection and annotation, potential subjectivity in labeling, and inter-observer variability, which can impact model accuracy and reliability. Additionally, CNNs may exhibit bias toward the training data distribution, leading to poor generalization on diverse patient populations and varying imaging conditions. Their interpretability remains a concern, as the complex learned features make clinical decisions difficult to explain and trust. Furthermore, CNNs are computationally intensive, limiting their scalability in resource-constrained environments. Integrating Agile methodology into DL implementation improves adaptability, collaboration, and continuous refinement through iterative cycles (sprints), allowing incremental model enhancements, frequent feedback, and flexibility in optimizing preprocessing, training, and evaluation. This approach strengthens medical image analysis by incorporating transfer learning and fine-tuning techniques, ensuring robust and efficient DL solutions.

Model Selection in Agile Development: Agile methodology allows iterative evaluation of different CNN architectures to determine the most effective one for biomedical image processing. The development team can start with a baseline model, such as ResNet or VGG, and refine choices based on sprint feedback. Each iteration tests a model's performance on medical datasets, ensuring flexibility in selection. Frequent reviews and stakeholder input guide adjustments, improving efficiency in choosing the best architecture. If a model underperforms, Agile enables a quick pivot to alternative options without delaying development. This iterative approach enhances accuracy while minimizing computational overhead.

Preprocessing with Agile Iterations: Preprocessing in Agile is continuously refined through iterative experiments on noise reduction, contrast enhancement, and normalization techniques. Each sprint tests different preprocessing strategies, assessing their impact on model accuracy and image quality. Agile ensures adjustments are made dynamically based on validation results and stakeholder feedback. If a technique fails to enhance performance, a new approach is tested in the next sprint. This iterative refinement prevents bottlenecks and improves image input quality. Agile's flexibility ensures that preprocessing methods remain optimized for evolving dataset challenges.

Training Strategy in Agile Workflow: Agile-driven training involves iterative fine-tuning of hyperparameters, transfer learning, and data augmentation techniques. Initial sprints focus on training a model with a small dataset to quickly evaluate performance trends. Subsequent iterations refine batch size, learning rates, and augmentation strategies to enhance generalization. Regular sprint reviews ensure early identification of overfitting or underfitting issues, preventing wasted computational resources. The model evolves progressively, with improvements applied based on continuous validation feedback. Agile ensures that training strategies remain adaptable to dataset variations and computational constraints.

Evaluation and Continuous Feedback: Agile emphasizes frequent evaluation using key performance metrics like accuracy, sensitivity, specificity, and processing time. Each sprint ends with model testing, allowing immediate feedback and necessary refinements. If a metric shows suboptimal performance, adjustments are made in the next cycle. Stakeholder and domain expert input ensures the model aligns with clinical requirements. Continuous monitoring enables quick identification and resolution of issues, improving reliability. Agile-driven evaluations ensure the DL model remains effective and adaptable to real-world medical applications. The overall flow diagram is shown in figure 1.

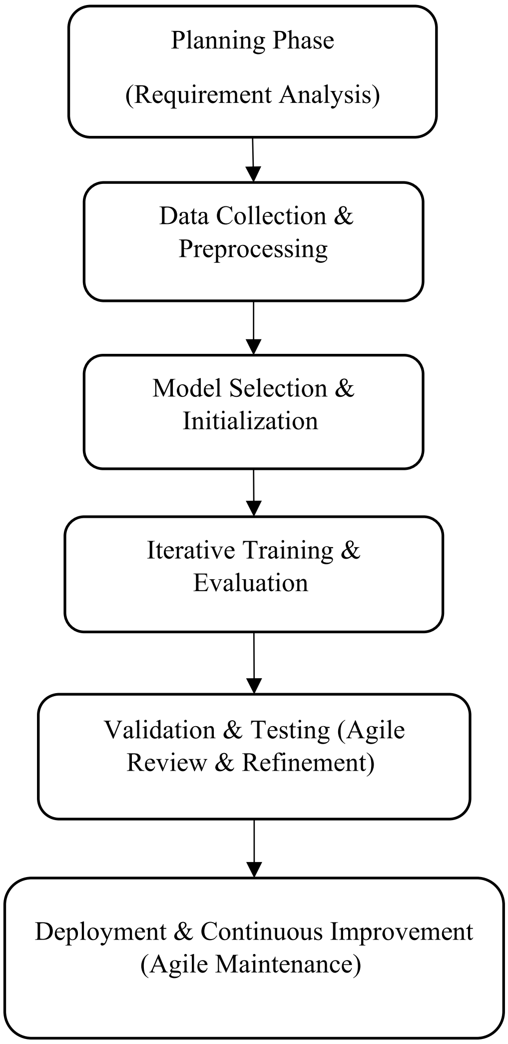

FIGURE 1. Overall flow diagram of biomedical image processing

Evaluation Parameters: Evaluating a DL model for biomedical image processing requires a comprehensive analysis of its predictive performance, reliability, and efficiency. Various evaluation metrics are used to assess the model's ability to classify medical images accurately and effectively. Below are the key evaluation parameters, along with their detailed definitions:

Accuracy: Accuracy is the most basic evaluation metric that measures the proportion of correctly classified cases, including both diseased and healthy cases, out of the total number of cases. It provides a general performance measure but can be misleading when dealing with imbalanced datasets, such as cases where diseased images are much fewer than healthy images. In medical applications, accuracy alone is insufficient, as false negatives (missed disease cases) can have serious consequences.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Sensitivity: Sensitivity, also known as recall, measures how well the model correctly identifies diseased cases. A high sensitivity ensures that fewer cases go undetected, which is essential in medical diagnosis where missing a disease could lead to severe health risks. Sensitivity is particularly important for diseases requiring early detection, such as cancer or pneumonia. A model with high sensitivity minimizes false negatives, reducing the chances of missing critical conditions. However, improving sensitivity alone may increase false positives, which is why it is often balanced with specificity.

$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

Specificity: Specificity measures how well the model correctly identifies healthy cases, ensuring that individuals without the disease are not misclassified as having it. High specificity reduces false positives, preventing unnecessary treatments and reducing patient anxiety. This metric is crucial in applications were misdiagnosing a healthy person as diseased could lead to excessive medical interventions. A model with high specificity is useful in preventing overdiagnosis but should be balanced with sensitivity to ensure critical conditions are not overlooked.

$$\text{Specificity} = \frac{TN}{TN + FP}$$

Precision: Precision evaluates how many of the positive cases identified by the model are actually diseased. It is particularly useful in medical applications where false positives could lead to unnecessary treatments, additional tests, or anxiety for patients. A high precision means that most of the detected disease cases are actually correct, reducing the rate of misdiagnosis. While sensitivity ensures that diseased cases are not missed, precision ensures that detected positive cases are truly diseased, making it a crucial metric for balancing diagnostic accuracy.

$$\text{Precision} = \frac{TP}{TP + FP}$$

F1-Score: F1-score is the harmonic mean of precision and sensitivity, providing a balanced evaluation of the model's performance. It is particularly useful when the dataset is imbalanced, ensuring that both false positives and false negatives are minimized. A high F1-score indicates that the model effectively detects disease cases while maintaining precision. A model with a high F1-score is well-balanced and reliable, making it suitable for medical applications where both correct detection and minimal false alarms are critical.

$$F1_{measure} = 2 * \frac{Precision * Recall}{Precision + Recall}$$

Area Under the Receiver Operating Characteristic Curve (AUC-ROC): Across various classification thresholds, the model's capacity to differentiate between ill and healthy instances is assessed by the AUC-ROC curve. The true positive rate (sensitivity) and false positive rate (1-specificity) are shown against each other on the ROC curve, and the model's overall performance is indicated by the area under the curve (AUC). The model successfully distinguishes between healthy and ill cases when the AUC value is high (nearer to 1). Since AUC-ROC offers a comprehensive assessment of the accuracy of classification across all threshold values, it is a crucial parameter for comparing various models.

$$\text{AUC-ROC} = \int_{False\ Positive\ Rate=0}^{1} \text{True Positive Rated(False Positive Rate)}$$

Computational Efficiency (Memory and Hardware Utilization): Computational efficiency measures the amount of hardware resources (such as GPU/CPU usage, memory consumption, and power consumption) required by the DL model during training and inference. High resource usage can limit the model's deployment in real-world medical settings, particularly on edge devices or cloud-based platforms. Models with high computational efficiency offer a good balance between performance and resource utilization, making them suitable for real-time medical applications.

$$\text{Computational Efficiency} = \frac{Model\ Accuracy}{Computational\ Cost}$$

4. CONCLUSION

The agile deep learning-based biomedical image processing framework enhances diagnostic accuracy and efficiency while addressing limitations of traditional methods. By leveraging CNNs and iterative refinements, it ensures improved anomaly detection, faster processing, and adaptability across diverse imaging modalities. Unlike conventional approaches, which often struggle with scalability and evolving medical requirements, this method integrates real-time updates and robust feature extraction for precise classification. The framework's flexibility supports continuous optimization, making it suitable for clinical applications requiring high reliability. Experimental validation demonstrates superior performance in automated medical diagnosis, reinforcing deep learning's role in modern healthcare. Its adaptability facilitates seamless integration into diagnostic workflows, assisting medical professionals in decision-making. The approach effectively handles variations in image quality and complex pathological patterns, ensuring consistent results. Additionally, the agile-driven methodology accelerates deployment cycles, reducing delays in implementing advancements. Future research may focus on expanding dataset diversity and refining computational efficiency to further enhance scalability. The findings underscore the transformative potential of DL in biomedical imaging.

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