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The Utilization of Artificial Intelligence in Healthcare: Review, Challenges, and Future Research

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ABSTRACT

Integrating Artificial Intelligence (AI) into the healthcare system has made major progress for diagnosing disease, patient monitoring, and medical imaging, creating a highly interconnected ecosystem for improved medical decision-making. AI-driven disease diagnosis utilizes machine learning models to analyze vast medical datasets, enabling quick and precise identification of diseases. This diagnostic capability is further enhanced by AI-powered medical imaging, where deep learning techniques, including convolutional neural networks (CNNs), refine image analysis, segmentation, and classification, providing critical support for precise diagnosis. Alongside these deep learning techniques, support vector machines (SVMs) offer strong classification powers that work especially well in situations requiring high-dimensional data processing with sparse training data. By combining CNNs for obtaining features and SVMs for categorizing, the advantages of both methods are combined to increase computational efficiency and diagnostic certainty. These AI-based insights are then reinforced through patient monitoring, where wearable sensors and IoT devices continuously track patient health, feeding real-time data into AI models that detect anomalies and predict disease progression. The synergy between these three areas ensures a continuous flow of medical information, enhancing predictive analytics and personalized treatment strategies. This review examines how powered system AI unifies disease diagnosis and patient monitoring using medical imaging into an integrated healthcare system, discussing current challenges such as data security, interpretability, and clinical adoption. The findings highlight AI's role in bridging diagnostic precision, real-time monitoring, and advanced imaging, paving the way for a more proactive and efficient healthcare framework.

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1. Introduction

The healthcare industry is currently facing complex and pressing challenges, including a rapidly increasing patient population, limited medical resources, and the demand to improve efficiency and accuracy in diagnosis and treatment. The increasing incidence of long-term diseases, such as cancer, diabetes, and cardiovascular disorders, has placed an enormous burden on healthcare providers, often resulting in delayed diagnosis, misdiagnoses, and suboptimal treatment strategies. These challenges are exacerbated due to the overwhelming amount and intricacy of medical data, which include electronic health records (EHRs), laboratory test results, genetic profiles, and medical imaging including X-rays, Computed Tomography (CT) scans, and MRIs. Healthcare professionals must analyze and interpret these diverse datasets to make informed clinical judgements, yet the increasing workload and demand for precision make traditional diagnostic methods inefficient [1].

For instance, in disease diagnosis, physicians rely on imaging techniques such as radiology and pathology, which require highly trained specialists to examine images manually. However, human mistakes, time constraints, and disparities in knowledge may lead to varying interpretations. leading to misdiagnoses or delayed treatments [2]. Similarly, in patient monitoring, it is necessary to continuously assess vital indicators such as heart rate, blood pressure, and glucose levels, especially for high-risk patients. However, conventional monitoring systems often fail to provide real-time insights or predictive analysis to anticipate possible complications before they become serious [3].

Considering these difficulties, artificial intelligence (AI) has emerged as a game-changing medical technology. AI offers solutions that can automate complex data analysis, improving diagnostic accuracy, developing treatment planning, and supporting real-time patient monitoring are important steps in the medical world [4]. One of the most successful applications of artificial intelligence is seen in the field of medical imaging. This is where deep learning models, especially convolutional neural networks (CNNs), have shown remarkable capabilities in detecting tumors, fractures, and cardiovascular abnormalities with a level of precision comparable to or even exceeding that of human radiologists [5]. For example, AI-based imaging systems have been utilized to detect retinal illnesses in ophthalmology and identify lung cancer nodules on CT scans, greatly increasing the early detection rate [6].

Beyond imaging, AI has also revolutionized clinical decision support systems (CDSS) by integrating EHRs, genetic data, and predictive analytics to assist doctors in personalizing treatment plans and assessing disease risks [7]. In precision medicine, AI helps analyze genetic mutations to determine the most effective therapy for individual patients, thereby reducing trial-and-error treatment approaches and improving patient outcomes [8]. AI-powered wearable devices and Internet of Things (IoT) monitoring systems further enable real-time tracking of vital signs, early detection of anomalies, and predictive alerts for medical emergencies, reducing hospital readmissions and improving chronic disease management [9].

Despite its vast potential, the adoption of artificial intelligence (AI) in healthcare is certainly not without its challenges. One of the main concerns is the lack of interpretability and transparency in AI models. Many deep learning algorithms operate as black boxes, which makes it difficult for healthcare professionals to understand the basis of AI-generated diagnoses. In addition, the issue of data privacy and security is also a very important concern. Given that AI relies on large volumes of sensitive patient information, making it susceptible to cyber threats and ethical concerns regarding patient confidentiality [10]. Moreover, disparities in AI adoption persist, especially in low- and middle-income countries (LMICs), where access to AI-driven healthcare innovations is limited due to insufficient infrastructure, regulatory constraints, and a shortage of AI expertise [11].

To fully realize AI's potential in healthcare, it is crucial to address these challenges through enhanced model transparency, strong data security protocol, and the development of ethical AI frameworks. Future research should focus on human-in-the-loop AI systems, in which AI serves as an assistive tool rather than a replacement for medical professionals, ensuring that AI complements clinical expertise while maintaining a patient-centered and ethical healthcare approach [12].

This objective of the paper to explore the growing role of AI in the healthcare sector. analyzing its applications, benefits, and challenges while emphasizing the importance of ethical AI implementation, regulatory policies, and equal access to artificial intelligence-based healthcare solutions. By advancing research in AI-assisted diagnostics, treatment planning, and real-time monitoring, healthcare systems can move toward a more efficient, accurate and customized approach to patient care.

The following section discusses relevant studies in the topic of (AI) in healthcare and examples of its application. Section 3 discusses the methodology used in medical imaging. Especially, we evaluated and compared research methods, algorithms, and datasets from other researchers that address key performance indicators, for example sensitivity, accuracy specificity, and AUC-ROC in medical imaging, disease diagnosis, and patient monitoring in Sec. 4. Based on the experimental results and analyses that have been carried out using various algorithms, Sec. 5 discusses the key findings, their implications, and the challenges associated with AI applications in healthcare. Building on the findings and discussions from previous sections, Sec. 6 presents the conclusions drawn from the study and explores future directions for AI applications in healthcare. Finally, Sec. 7 outlines the key mathematical formulations and equations that underpin the development and evaluation of the AI models discussed in this study.

2. Related Works

2.1 Medical Imaging

Medical imaging has been significantly altered by the integration of Artificial Intelligence (AI) and Machine Learning (ML). Several studies have demonstrated how AI improves diagnostic accuracy, speeds up analysis, and enhances decision-making in radiology and other medical fields.

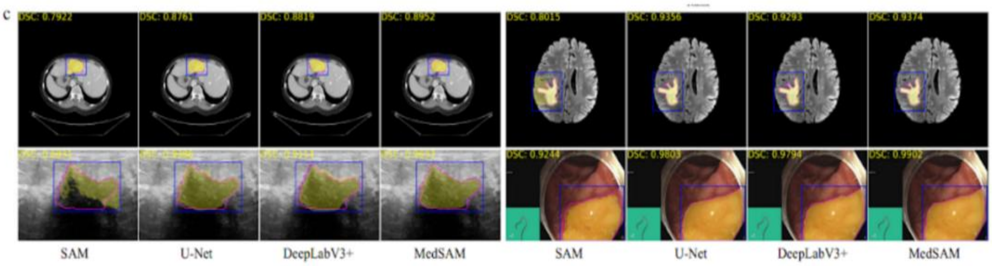

Fig 1. Visualizations showcasing segmentation examples for various cancers and medical imaging modalities, while the performance distribution is illustrated through box plots and podium plots that highlight the median, percentiles, and frequency of ranks achieved by different methods [13].

Medical imaging research has significantly advanced with the integration of artificial intelligence (AI) to enhance diagnostic accuracy and clinical efficiency. The Breast Screening-AI study by [14] evaluates the impact of AI-assisted diagnosis in breast cancer screening by comparing two scenarios: Clinician-Only and Clinician-AI. The findings demonstrate that incorporating AI reduces diagnostic errors, with a 27% decrease in false positives and a 4% reduction in false negatives. Additionally, AI integration improves workflow efficiency, reducing diagnosis time by an average of three minutes per patient, while 91% of clinicians reported increased contentment and having more faith in the system . Beyond accuracy, the study emphasizes the importance of explainability in AI-driven diagnostics. By providing visual explanations through heatmaps, the system enhances clinicians' understanding and trust in AI-generated recommendations. This highlights the need for AI model that is not only accurate, but also easy to use and transparent. The Breast Screening-AI framework demonstrate effective ways to integrate AI into clinical work processes, offering a valuable tool to support medical decision-making in real-world healthcare environments[15]. In addition to improving diagnostic accuracy, the integration of AI in medical imaging also fosters collaboration between clinicians and technology. By streamlining workflows and providing actionable insights. AI tools empower healthcare professionals to focus more on patient care rather than administrative tasks. AI continues to evolve, supporting clinical teams and will likely expand, opens up opportunities for more personalised and effective healthcare solutions.

2.2 Disease Diagnosis

Diagnosis is generally organized into a structured process that aims to identify medical conditions based on clinical findings [16]. The process includes symptom assessment as the initial stage, physical examination of the patient, which is the doctor's action to assess symptoms from physical signs. If necessary or require further studies are required, including laboratory tests and imaging studies. Other diagnostic assessments can be done by reviewing both personal and family medical history, as well as the clinical reasoning of the doctor to reach a diagnosis [17]. AI and machine learning help to improve this with their ability to process and analyze big data to produce accurate diagnoses [18]. AI plays an important role in medical imaging by providing a detailed view of the body with tools. For instance, during the Corona Virus Disease (COVID-19) pandemic—first identified in Wuhan and now a global health threat—the primary diagnostic method relies on RT-PCR (Real Time Polymerase Chain Reaction) tests, using nasopharyngeal swabs to detect severe acute respiratory syndrome-related coronavirus (SARS-CoV-2)-specific genes [19]. While traditional techniques like RT-PCR [20]remain foundational, AI supports diagnostics by interpreting imaging results , predicting disease spread, or optimizing test result analysis [21]. This integration of technology exemplifies how AI complements conventional methods to advance precision and efficiency in modern healthcare. AI is able to prioritise the need for ventilators and respiratory support in intensive care units by analysing data obtained from clinical parameters. This can provide crucial information that supports more informed resource allocation and decision-making [22]. Using Chest X Ray (CXR) and Computed Tomography (CT) images, AI was utilized to detect and quantify COVID-19. AI can also be utilized to provide daily updates, perform storage and trend analysis., as well as to monitor the course of treatment and forecast the likelihood of recovery or mortality in COVID-19 [23].

2.3 Patient Monitoring

Remote patient monitoring (RPM) is a growing field in healthcare. This innovation is designed to provide support for doctors in providing care in various medical rooms as well as general surgery. RPM utilises flexible materials for sensors that can serve to efficiently expand patient monitoring capabilities[9]. As a result of the COVID-19 pandemic, telehealth became a common strategy for maintaining patients' and clinicians' safety [23]. Machine learning and image processing techniques played a vital role in telehealth monitoring. The AI methods are capable of monitoring patients vital signs such as heart rate, respiratory rate, oxygen saturation (SpO2), cough analysis, and blood pressure. Rohmetra surveyed AI-powered telehealth monitoring of vital signs has demonstrated advantages over traditional methods. Utilising image and video processing techniques in machine learning (ML), the system is able to identify regions of interest (ROI) on patients, such as facial features, and then focus on these areas to estimate vital signs, including heart rate and respiratory rate. Developing deep learning models, specifically convolutional neural networks (CNN), capable of recognising individuals' psychological stress levels[13], [24]. Patient monitoring techniques via telehealth have great potential in diagnosing patients' health conditions. By utilising AI telehealth monitoring can be a more effective approach in classifying or predicting patients' vital signs [9]. In hospitals, medical staff routinely monitor patients' health conditions and document them manually. The collection of patient vital signs is done manually and is influenced by various factors, including clinical workload, staff working hours, patient diagnosis, clinical leadership, and applicable national guidelines [1] and was limited due to the lack of resources. Monitoring patients has traditionally been done using invasive devices that require direct skin contact to assess their vital signs. However, technological advancements in data transmission have changed the landscape of the healthcare industry, bringing non-invasive devices that do not need to touch the patient's body, allowing for continuous monitoring. These innovations have revolutionised the way we traditionally monitor patient health, giving patients the opportunity to monitor their health conditions remotely, whether in a hospital, care facility or in their own homes[25]. In this section, we will discuss the Remote Patient Monitoring (RPM) architecture that supports these technologies [26].

2.4 Convolutional Neural Network

Convolutional neural networks (CNNs) are extremely useful for diagnosing diseases from medical pictures like MRIs and X-rays because oftheir remarkable capacity to manage image data [1]. Convolutional neural networks (CNNs) and data mining methods are used in deep learning to add layers that aid in finding patterns in the data. deep learning models created especially for handling structured grid data, such as pictures [27]. CNNs extract information and develop complex representations from high-dimensional data by combining convolutional, pooling, and fully connected layers [28]. CNN, also referred to as ConvNet, is a popular kind of Artificial Neural Network (ANN) that is categorized as a supervised technique. This approach is renowned for its capacity to identify and decipher patterns. CNN is helpful for image analysis, where multiple techniques are employed to construct one image, because of its ability to recognize patterns [29]. These parameters include radiation absorption in X-ray imaging, sound pressure in ultrasound, and high frequency signal capacity in an MRI [30]. While several measurements are gathered for multichannel imaging, each pixel in a digital image is determined by a single measurement. Diagnostic images are created using a range of imaging modalities, such as computed tomography (CT), X-ray, magnetic resonance imaging, and functional magnetic resonance imaging (MRI and fMRI). positron emission tomography, Image classification, segmentation, rsynthesis, and regression are common DL applications with medical imaging [31]. Many medical diseases require medical imaging for diagnosis and monitoring, and the interpretation of these pictures has historically depended significantly on the knowledge of radiologists and other medical experts, which can be laborious and prone to human mistake [32]. CNNs excel at this role by automatically distinguishing organs or lesions from surrounding tissues in images, allowing surgeons to plan and perform surgeries more precisely. CNNs have proven effective in the diagnosis and detection of a wide range of illnesses, such as neurological disorders, pneumonia, and other lung conditions, and cancer [33]. Popular CNN designs include VGGNet, ResNet, and Inception 9. Formula (1) defines the convolution process between two functions. F and G:

$$(f * g)(t) \stackrel{\text{def}}{=} \int_{-\infty}^{\infty} f(\tau)g(t - \tau)d\tau$$

The following are the variables and symbols used:

- $(f * g)(t)$: This shows how functions f and g are convolutional at point t.
- $f(\tau)$: This is a convolved function.
- $g(t - \tau)$: The second convolved function, with a shift of
- t : The variable used to evaluate the convolution result:
- τ : The integral's integration variable, which would indicate a possible change in the function g.

Formula (1) shows how shifting g across f alters the function g's influence on f. This process sheds light on the interactions and effects between these functions [34].

2.5 Support Vector Machine

Because of their capacity to represent intricate relationships between inputs and outputs, Support Vector Machines (SVMs) have grown in popularity in scientific image analysis [35]. SVMs are of exceptional quality because of their greater performance overall and their capacity to handle non-linear data in over-dimensional information units [31]. In clinical image analysis, SVMs are used in various packages, including tumor detection in magnetic resonance imaging (MRI) and lesion classification in computed tomography (CT). SVM is a machine learning tool that uses the concept of data classification as its foundation. To classify the data, it builds an N-dimensional hyperplane that divides it into two groups as efficiently as possible, linear and non-linear [35]. The dot product is the default kernel function, which transfers the training data into a kernel space. For non-linear cases, SVM uses a kernel function that plays a role in mapping the data into different spaces, thus allowing the separation of data even with very complex boundaries [36].

3. Methodology

This study employs a comprehensive approach to explore the application of AI in healthcare, especially focuses on its important role in diagnostics, treatment planning, and real-time patient monitoring. The methodology used is composed of several key components, such as data collection, algorithm selection, experimental design, and analysis. Our research flow can be seen at Figure 2.

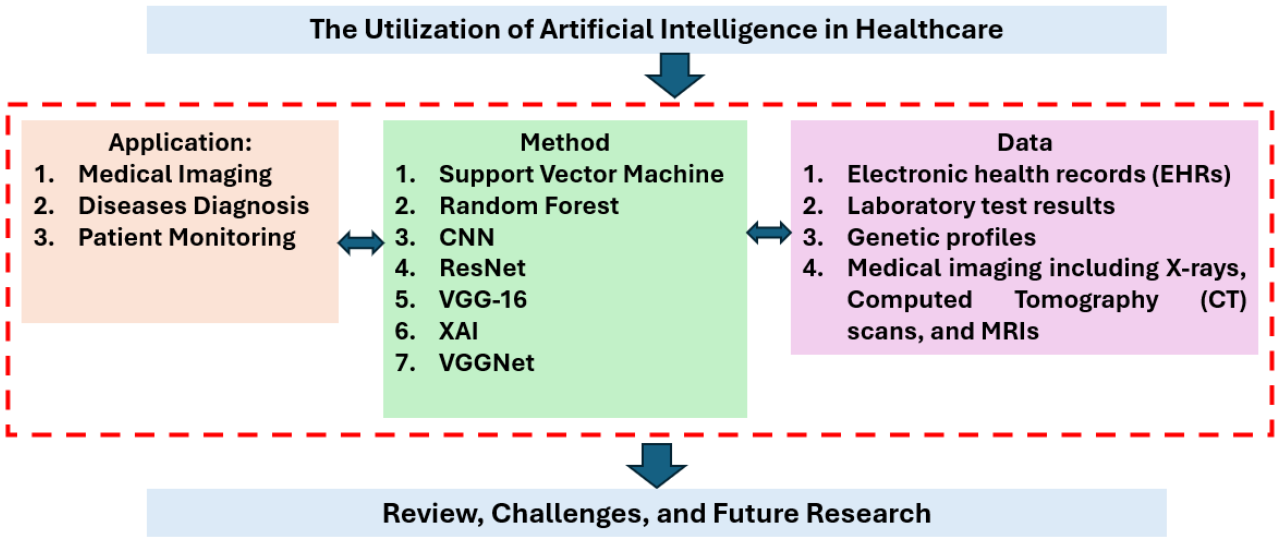

Fig 2. Research workflow.

The diagram on Figure 2 illustrates the utilization of Artificial Intelligence (AI) in healthcare by highlighting its applications, methods, and types of data involved. AI is applied in three major areas: medical imaging, disease diagnosis, and patient monitoring. These applications are supported by various AI methods, including traditional machine learning algorithms such as Support Vector Machines and Random Forests, as well as deep learning models like Convolutional Neural Networks (CNNs), ResNet, VGG-16, and VGGNet. Additionally, Explainable AI (XAI) plays a role in ensuring interpretability and transparency of the models. The effectiveness of these methods depends on the diverse healthcare data they process, which includes electronic health records (EHRs), laboratory test results, genetic profiles, and medical imaging data such as X-rays, CT scans, and MRIs. Overall, this framework emphasizes how AI integrates applications, methods, and data sources to advance healthcare, while also pointing to the need for continued review, addressing challenges, and exploring future research directions.

3.1 Data Collection

We explored a range of datasets covering some medical fields to study the impact of AI in healthcare.

3.1.1 Medical Imaging Data

In the field of medical imaging, open-access datasets with annotated images are very important, especially for diseases of the retina and lung cancer. For instance, datasets featuring lung cancer nodules derived from *CT* scans provide a wealth of information that deep learning models can use as training data. These images are meticulously labeled to indicate the presence of nodules, which allows researchers and developers to create algorithms that can accurately identify and classify these potentially malignant growths.

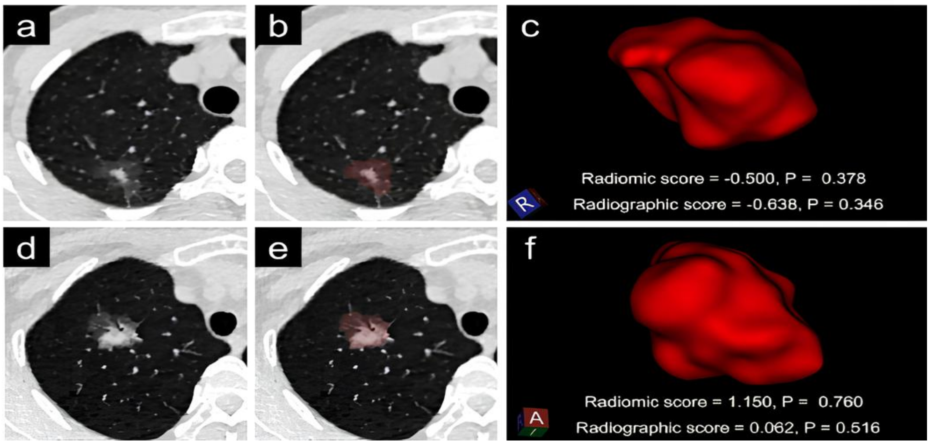

Fig 3. Representative images and segmentation results of nodules. (a, b, c) A 52-year-old male with low-risk lung adenocarcinoma. (d, e, f) A 56-year-old female with high-risk lung adenocarcinoma. For the radiomic model, the threshold values for predicting high-risk lung cancer were 0.387, and for the radiographic model, the values were 0.364 [11].

The significance of these datasets extends beyond mere image collection. They are foundational for deep learning model training and validation, with a focus on Convolutional Neural Networks (CNNs). CNNs can automatically learn hierarchical features from raw pixel data, which makes them particularly ideal for image analysis. Various architectures of CNNs have been developed to enhance performance in medical imaging tasks. For example, ResNet (Residual Network) introduces skip connections that allow gradients to flow more easily during training, enabling the construction of very deep networks without suffering from the vanishing gradient problem. This architecture has been widely adopted for tasks such as lung nodule detection, where depth and feature extraction are crucial. As shown in Figure 4, the architecture of the FA-ResNet and the FA-Res module proposed by [12] further builds upon this foundation to improve accuracy and robustness in medical imaging applications.

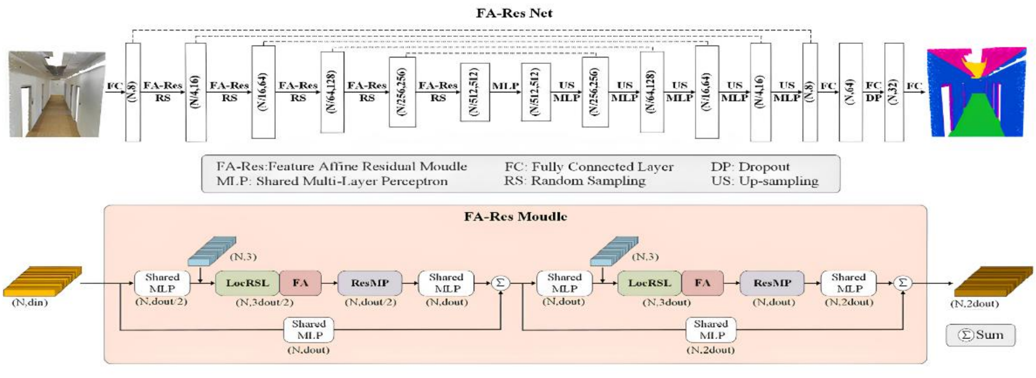

Fig 4. Architecture of the FA-ResNet (top) and FA-Res's module (bottom) [12]

EfficientNet is another notable architecture that optimizes the balance between network width, depth, and resolution. In order to achieve great performance with fewer parameters, EfficientNet employs an effective scaling technique that balances the model's depth, width, and resolution. This makes it ideal for classifying medical images, such as identifying retinal disorders. Because of its high efficiency, it runs and trains more quickly, which is crucial in clinical settings where every second counts. As illustrated in Figure 5, the general workflow of the proposed method based on EfficientNet [37] highlights the streamlined and scalable approach that underpins its effectiveness in medical image analysis.

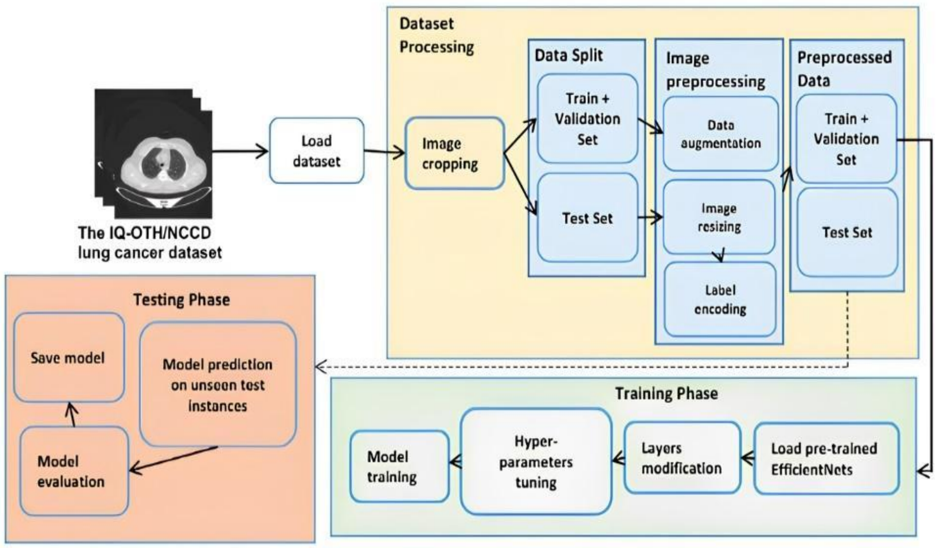

Fig 5. The general workflow of the proposed method, Efficient Net [37].

Medical imaging also uses conventional machine learning methods such as Support Vector Machines (SVM) in addition to CNNs. For classification jobs where the dataset is smaller or when the features have been extracted using CNNs, SVMs are especially beneficial. SVMs can efficiently classify images based on the features learned from the annotated datasets by locating the best hyperplane separating several classes in the feature space.

Because it directly influences how well AI-driven diagnostic tools operate in clinical environments, this training and validation approach is essential to improve patient outcomes. Combining modern CNN architectures with conventional machine learning techniques such as SVMs offers a strong framework for addressing difficult medical imaging problems, therefore opening the door for creative healthcare solutions.

The healthcare industry is currently facing complex and pressing challenges, including a rapidly increasing patient population, limited medical resources, and the demand to improve efficiency and accuracy in diagnosis and treatment. The increasing incidence of long-term diseases, such as cancer, diabetes, and cardiovascular disorders, has placed an enormous burden on healthcare providers, often resulting in delayed diagnosis, misdiagnoses, and suboptimal treatment strategies. These challenges are exacerbated due to the overwhelming amount and intricacy of medical data, which include electronic health records (EHRs), laboratory test results, genetic profiles, and medical imaging including X-rays, Computed Tomography (CT) scans, and MRIs. Healthcare professionals must analyze and interpret these diverse datasets to make informed clinical judgements, yet the increasing workload and demand for precision make traditional diagnostic methods inefficient.

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To fully realize AI's potential in healthcare, it is crucial to address these challenges through enhanced model transparency, strong data security protocol, and the development of ethical AI frameworks. Future research should focus on human-in-the-loop AI systems, in which AI serves as an assistive tool rather than a replacement for medical professionals, ensuring that AI complements clinical expertise while maintaining a patient-centered and ethical healthcare approach [12].

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3.1.2 Electronic Health Records (EHRs)

Accessing de-identified Electronic Health Record (EHR) datasets is a crucial step in advancing healthcare research and improving patient care. These datasets typically include a wealth of information, such as patient demographics, which encompass age, gender, ethnicity, and socioeconomic status. Understanding these demographic factors is vital, as they can significantly influence health outcomes and treatment responses [9]. For instance, certain diseases may manifest differently across various demographic groups, and recognizing these differences can lead to more personalized and effective treatment plans. In addition to demographics, de-identified EHR datasets contain comprehensive medical histories of patients. This includes information about past illnesses, surgeries, medications, allergies, and family medical history. Such detailed records allow researchers and healthcare professionals to identify patterns and correlations that may not be immediately apparent. For example, analyzing the medical histories of patients [42] with similar conditions can help uncover risk factors or commonalities that could inform future treatment strategies. Moreover, treatment outcomes are a critical component of these datasets. This information reflects the effectiveness of various interventions and therapies, providing insights into what works best for specific patient populations. Researchers are able to build predictive models that predict how many different patients may react to specific treatments based on their individual traits and medical histories by analyzing treatment outcomes. In clinical settings, these models can be useful in helping healthcare professionals make well-informed decisions on patient care. A further significant benefit is the integration of this rich data into clinical decision support systems. These systems use cutting-edge algorithms and machine learning methods to evaluate EHR data and give medical professionals advice in real time [1]. For example, based on a patient's medication history, a clinical decision support system may notify a doctor about possible drug interactions or suggest different treatment options based on the patient's medical history and demographics. In summary, accessing de-identified EHR datasets that include patient demographics, medical history, and treatment outcomes is essential for developing predictive models and clinical decision support systems. This data not only enhances our understanding of patient populations but also empowers healthcare providers to deliver more personalized and effective care, ultimately leading to improved health outcomes [43].

3.1.3 Wearable Device Data

In the medical field, data gathered from wearable health monitoring devices is becoming more and more important, especially for real-time vital sign tracking and its consequences for patient management. These gadgets, which include fitness trackers and smartwatches, continuously monitor vital signs, including blood pressure, oxygen saturation, and heart rate. Health care providers are able to quickly learn about a patient's health status thanks to this real-time data, letting them take prompt actions when needed. The continuous monitoring capability of wearables offers significant advantages over traditional methods, which often rely on periodic checkups. For example, sudden changes in vital signs, such as an elevated heart rate or decreased oxygen levels, can be detected immediately, prompting healthcare professionals to take action [40]. Additionally, integrating this data into electronic health records (EHRs) provides a comprehensive view of a patient's health history, allowing for better-informed clinical decisions. Beyond individual patient management, real-time vital sign tracking from wearables can improve population health outcomes. By aggregating data from multiple patients, healthcare organizations can identify trends that may indicate broader public health issues, such as an outbreak of illness. As technology advances, the integration of wearable data into healthcare systems is expected to play a crucial role in enhancing health outcomes and optimizing patient management strategies [9], [43].

3.2 Algorithm Selection

Given the complexity of the datasets, several AI algorithms to evaluate performance in different healthcare applications

3.2.1 Convolutional Neural Networks (CNNs)

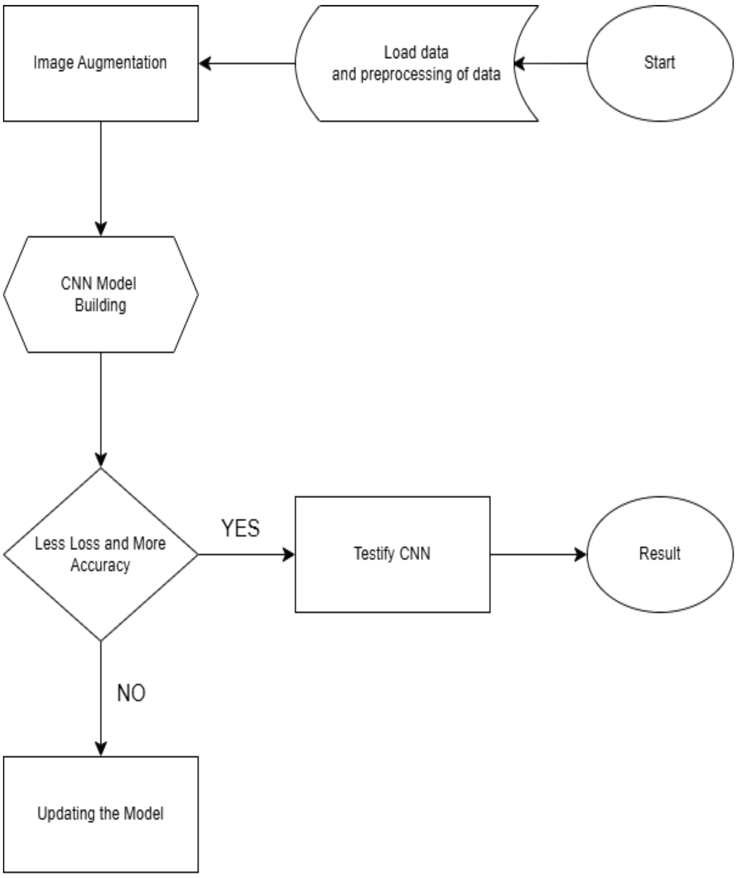

Fig 6. Steps for detection using CNN [44].

Convolutional neural networks are most frequently used for image processing tasks, particularly the identification of tumors in medical pictures. CNNs' ability to automatically extract features from images is perhaps their most alluring feature. This makes them ideal for understanding complex visual information. This is a great advantage of medical imaging since it gives the ability to identify minute patterns and anomalies that may indicate the existence of tumor or other disease conditions [45], [46].

CNNs operate through a series of layers that process the input image in a hierarchical manner. The initial layers typically focus on detecting simple features such as edges and textures, while deeper layers progressively capture more complex patterns, such as shapes and specific structures within the image. This hierarchical feature extraction is particularly beneficial in medical imaging, where the visual characteristics of tumors [46] can vary significantly based on their type, size, and location. For instance, a CNN trained on a dataset of mammograms [33] can learn to differentiate between benign and malignant masses by recognizing specific features associated with each [28].

The training process of CNNs involves using large, annotated datasets, which are essential for teaching the model to recognize and classify different types of tumors accurately. These datasets often include thousands of labeled images, allowing the CNN to learn from a diverse range of examples. As the model trains, it adjusts its internal parameters so that the gap between its outputs and the real labels decreases to make it progressively more accurate over time. It is this supervised learning that plays a crucial role in developing successful diagnostic tools that can assist oncologists and radiologists in making correct decisions regarding patient care [33], [43].

In summary, CNNs have become a building block in the analysis of medical images, particularly when it concerns tasks such as tumor detection. By virtue of their ability to automatically extract and learn image features, they have the capability of identifying complex patterns that may be indicative of several medical conditions. Through ongoing study and development, uses of CNNs in imaging medicine will no doubt extend far and wide in generating more effective and accurate diagnoses that can pave the way towards improved patient results [47].

3.2.2 Random Forest and Support Vector Machine (SVM)

Random Forest and Support Vector Machines (SVM) are among the most popular machine learning algorithms in healthcare, especially when dealing with structured data from Electronic Health Records (EHRs). These algorithms have achieved great success in a range of predictive tasks, including patient outcome prediction, chronic disease risk prediction, and clinical decision support.

An ensemble learning approach called Random Forest builds numerous decision trees and aggregates their results to improve forecast stability and accuracy [48]. Because it can manage non-linear interactions, overfitting robustness, and the provision of feature importance scores that encourage clinical interpretability, it is well-suited to manage complicated medical datasets.

SVM, on the other hand, is known for its effectiveness in high-dimensional data classification, such as genomic expressions and medical imaging. By applying kernel functions, SVMs can build non-linear decision boundaries, making them useful for distinguishing between clinically similar but statistically distinct conditions [49] .

The use of these algorithms in medical prediction systems is growing rapidly due to their high accuracy and robustness against outliers. Several studies have shown that Random Forest and SVM often outperform traditional methods in the early detection of diseases such as cancer, diabetes, and cardiovascular conditions [48], [50]

3.3 Experimental Design

3.3.1 Training and Validation

To enable the model to learn from the data in a quick way, the models were trained on various subsets of the data. This is normally conducted in machine learning. A section of the data is provided to the model during training so that the model finds patterns and relationships. Still another set is utilized to make an approximation of how well the model performs. Since the model has never seen this validation data before it was trained, it is an asset for verifying how well the model performs with new, unseen data. Overfitting, in which the model learns the training data but has difficulty learning anything new, can be avoided by maintaining separate training and validation data.

We used methods like cross-validation to additionally increase the validity of the outcomes. Using a robust statistical technique called cross-validation, a model's performance is estimated by splitting the dataset into different subsets, or "folds." As is customary in k-fold cross-validation, the dataset is divided into k equal parts. The model is then trained on k-1 of these parts and validated on the remaining part. This process is repeated k times, with each fold serving as the validation set once. The final performance metric is usually the average of the results obtained from each of the k iterations. By its approach of validating the model through testing it across several subsets of data, it not only provides a broader critique of how well the model works but also avoids overfitting. Cross-validation allows the model to work across varied portions of a dataset, something that comes in handy if the data turn out to be limited or biased. All else being equal, learning on a subset of the dataset, applying a different validation set, and using cross-validation techniques help construct a stronger, more robust model that can be used effectively under real-world scenarios.

3.3.2 Performance Metrics

Performance of models is evaluated based on a variety of different metrics like area under receiver operating characteristic curve (AUC-ROC), sensitivity, specificity, and accuracy. All the above parameters provide good information about the diagnostic potential of models, allowing scientists and doctors to know how well the models recognize and classify issues, such as medical malignancies.

One of the simplest measures is accuracy, which is the proportion of actual outcomes (both true positives and true negatives) out of all of the cases that were analyzed. That is, it calculates how frequently the model predicted correctly. Although accuracy is a helpful metric, it may be deceptive, particularly if the data is unbalanced and one class (e.g., tumor patients) greatly outnumbers the other class (e.g., healthy patients). In this situation, a model can get high accuracy by always predicting the majority class, without necessarily being good at recognizing the minority class.

Sensitivity, also known as recall or true positive rate, measures the model's ability to correctly identify positive cases, such as patients with tumors. It is calculated as the number of true positives divided by the sum of true positives and false negatives. A high sensitivity indicates that the model is effective at detecting the condition, which is particularly important in medical contexts where missing a diagnosis could have serious consequences.

Specificity of the model is an important part; it is an estimate of how well the model will be capable of correctly classifying negative cases, or healthy patients. The ratio of true negatives and false positives is divided by the number of true negatives to estimate it. To avoid unnecessary alarms, which lead to undue worry and additional tests for healthy patients, high specificity is necessary.

The other critical metric that gives a holistic view of how the model performs across different thresholds is the area under the receiver operating characteristic curve, or AUC-ROC. What the ROC curve actually does is it plots the true positive rate (sensitivity) versus the false positive rate (1 - specificity) at various threshold levels. The AUC quantifies the overall ability of the model to discriminate between positive and negative cases, with a value of 1 indicating perfect discrimination and a value of 0.5 suggesting no discrimination (equivalent to random guessing). A higher AUC value indicates a better-performing model.

In summary, using a combination of metrics such as accuracy, sensitivity, specificity, and AUC-ROC allows for a thorough assessment of the models' diagnostic capabilities. Each metric provides unique insights, and together they help to paint a complete picture of how well the models can identify and classify medical conditions, ultimately guiding improvements in patient care and treatment outcomes.

3.3.3 Real Time Monitoring Simulation

Simulated real-time monitoring scenarios were created to evaluate the effectiveness of AI in providing timely alerts for potential health issues. These simulations are designed to mimic actual healthcare environments where continuous monitoring of patients is essential, particularly for those with chronic conditions or those at risk of sudden health changes. By creating these scenarios, researchers can assess how well AI systems can analyze incoming data from various health monitoring devices and determine whether they can accurately identify potential health problems before they escalate.

In these simulated environments, data is generated in real-time, reflecting the types of vital signs and health metrics that would typically be collected from wearable devices, such as heart rate, blood pressure, oxygen saturation, and even glucose levels. The AI algorithms are then tasked with processing this data as it comes in, looking for patterns or anomalies that may indicate health issues. For example, if a patient's heart rate suddenly spikes or drops significantly, the AI system should be able to recognize this change and generate an alert for healthcare providers to investigate further.

The effectiveness of the AI system is evaluated based on several criteria. One key aspect is the timeliness of the alerts. The system must not only detect potential issues but also do so quickly enough to allow for prompt intervention. Delays in alerting healthcare providers can lead to worsening conditions or even life-threatening situations. Therefore, measuring the response time from the moment an anomaly is detected to when an alert is issued is crucial.

Another important criterion is the accuracy of the alerts. The AI must minimize false positives—alerts that indicate a problem when there is none—as these can lead to unnecessary anxiety for patients and additional strain on healthcare resources. Conversely, the system must also avoid false negatives, where a genuine health issue goes undetected. Both types of errors can have serious implications for patient safety and care.

Additionally, the simulations can help assess the user interface and usability of the alert system. It is essential that healthcare providers can easily understand and act upon the alerts generated by AI. This includes evaluating how the alerts are presented, whether they are clear and actionable, and how they fit into the existing workflow of healthcare professionals.

In summary, simulating real-time monitoring scenarios allows researchers to rigorously evaluate the effectiveness of AI in providing timely alerts for potential health issues. By analyzing the timeliness and accuracy of alerts, as well as the usability of the alert system, these simulations contribute to the development of AI technologies that can enhance patient care and improve health outcomes in real-world settings.

3.4 Data Analysis

3.4.1 Comparative Analysis

The best methods for particular healthcare applications were determined by comparing the performance of several algorithms on a range of tasks. The accuracy and effectiveness of diagnostic instruments, treatment suggestions, and patient management systems can all be greatly impacted by the algorithm used, which makes this comparative analysis essential in the healthcare industry. Researchers can ascertain which approaches produce the greatest results for tasks like disease detection, patient risk assessment, and treatment outcome prediction by methodically analyzing a variety of algorithms.

Other algorithms from other classes of machine learning and artificial intelligence were chosen to compare here. These are deep learning-based models like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) and more advanced methods like support vector machines (SVM), random forests, and more conventional statistical methods like logistic regression and decision trees. Since all algorithms harm the same way they benefit, it is necessary to evaluate the performance of the algorithm once implemented in certain healthcare tasks, for instance, predicting patient readmission or detecting tumors in medical images.

Pretrained datasets that have been split into training and test sets and are representative of the healthcare issue being addressed are generally used in the comparison process. The performance of every algorithm is measured using performance metrics like accuracy, precision, recall, and F1 score, and robust conclusions are obtained using methods like cross-validation. Additionally, factors like computational efficiency and scalability are considered, as algorithms must be able to process large volumes of data in real time, especially in critical scenarios like emergency care. Ultimately, this comparative analysis contributes to the development of more accurate, efficient, and reliable tools that enhance patient care and improve health outcomes.

3.4.2 Interpretability Assessment

Investigating the interpretability of AI models is a vital component of their implementation in healthcare, particularly when it comes to understanding how these models arrive at their decisions. This analysis is particularly significant for Convolutional Neural Networks (CNNs) utilized in medical imaging and for models that rely on Electronic Health Records (EHRs). Interpretability refers to how well a human can comprehend the reasons behind a decision made by an AI model. In the healthcare industry, where choices have a significant impact on patient outcomes, it is essential to make sure AI systems can be understood in order to promote patient and healthcare provider trust.

CNNs in medical imaging are frequently regarded as "black boxes" because they can analyze complex visual data and identify intricate patterns without offering clear explanations of how they arrive at specific predictions. For example, a CNN may be trained to identify tumors in radiological images, but it can be difficult to determine which aspects of the image contributed to a particular diagnosis. To tackle this challenge, researchers have created various methods to improve the interpretability of CNNs. Visualization techniques such as Grad-CAM (Gradient-weighted Class Activation Mapping), which highlight the areas of an image that had a major impact on the model's decision-making, are one popular method. By providing visual clarifications, these methods assist clinicians in grasping the reasoning behind the model's predictions, thereby boosting their confidence in AI-assisted diagnostics.

Conversely, EHR-based models typically depend on structured data, including patient demographics, medical histories, and lab results, to forecast patient outcomes or treatment suggestions. The decision-making processes of these models can also be intricate, particularly when they involve multiple variables and their interactions. To improve interpretability in EHR-based models, techniques such as feature importance analysis and decision trees can be utilized. Feature importance analysis identifies which variables most significantly affect the model's predictions, enabling healthcare providers to recognize the key factors that influence patient outcomes. Decision trees, in contrast, offer a clearer depiction of the decision-making process by visually outlining the paths taken based on various input variables, making it easier for clinicians to understand the logic behind the model's recommendations.

Moreover, assessing the interpretability of AI models, especially CNNs in medical imaging and EHR-based models, is important for knowing that healthcare professionals can rely on and utilize these technologies efficiently. By applying visualization techniques for CNNs and utilizing feature importance analysis or decision trees for EHR-based models, researchers can shed light on the decision-making processes of these AI systems. This level of transparency not only builds trust among users but also enhances clinical decision-making, ultimately resulting in better patient care and outcomes.

3.4.3 Ethical Considerations

The ethical considerations surrounding data privacy, security, and fair access to AI technologies in healthcare are especially crucial in low- and middle-income countries (LMICs). Concerns about the privacy of data stem from the risk of sensitive health information being misused, which is often worsened by insufficient informed consent and differing cultural views on privacy. Additionally, security issues arise from inadequate infrastructure to safeguard health data, leaving it exposed to cyber threats and breaches, particularly in areas without strong regulatory frameworks. These challenges underscore the necessity for a holistic strategy to protect patient information and uphold public confidence in healthcare systems.

Moreover, ensuring equitable access to AI technologies is a significant issue, as marginalized groups in LMICs encounter obstacles like poor internet connectivity and financial limitations, which can worsen existing health inequalities. To tackle these problems, it is vital to bolster regulations of data protection, improve cybersecurity practices, and encourage inclusive access to AI solutions. By focusing on these ethical aspects, healthcare systems can effectively utilize AI technologies to enhance health outcomes while honoring individual rights and promoting social equity.

4. Evaluation and Comparison of AI Models in Healthcare

4.1 Evaluation of Algorithm

Medical imaging has revolutionized disease diagnosis and treatment planning through advanced computational techniques [40]. Convolutional Neural Networks (CNNs) have become the backbone of image-based diagnostics, excelling in tasks like tumor detection in radiology and retinal disease classification in ophthalmology [51]. Support Vector Machines (SVMs), though traditionally used in medical imaging for classification problems, often require handcrafted features, making them less adaptable compared to deep learning approaches [36].

This review looks at several studies that use machine learning and deep learning algorithms for medical imaging, disease diagnosis, and patient monitoring to determine the usefulness of AI applications in healthcare. The evaluation is centered on essential performance indicators like accuracy, sensitivity, specificity, and AUC-ROC [52]. The various methods used by researchers, the algorithms used, and the performance results obtained are all reflected in this classification, which makes it pertinent. Table 1 describes the application of AI models in healthcare.

Table 1.
Application of AI models in healthcare.

Research Topic	Research Method	Dataset	Algorithm	Result
[18]	To enhance CNN tumor identification, this work uses several preprocessing methods, including bilateral filtering, K-means clustering, and Gaussian smoothing.	Brain MRI image dataset.	Resnet	Model evaluation based on accuracy metrics and the model's ability to highlight tumor areas.

[24]	In this work, CNN's performance in classifying skin lesions with and without pretreatment Region of Interest (RoI) extraction is compared.	Isic 2019 Dataset.	Multi Res Unet	According to the experimental findings, pre-processing increases the model training process's precision and effectiveness.
[32]	The use of pre-processing techniques such as histogram equalization and bilateral filtering to improve the accuracy of pneumonia detection using COVID-19.	a dataset of chest X-ray radiography (CXR) images	CNN Model	CNN's preprocessed model has a 94.5% accuracy rate, 98.4% sensitivity, and 98.0% specificity, compared to 88.0% for the unprocessed model.
[53]	To propose a solution to the Pneumonia problem, using a novel artificial neural network architecture. The proposed novelty consists of using dropouts on the convolution part of the network, tested on Kaggle medical images.	Kaggle: The lung ray images taken from Guangzhou Women's and Children's Medical Center	VCG-16	The achieved result is that the tested network obtained the following metrics: 97.2% accuracy, 97.3% recall, 97.4% precision, and AUC ¼ 0.982. and took first place in the Kaggle competition.
[36]	Quadtree decomposition is applied Recursively, before applying SVM on the subimages and ROIs identified by the model. ROIs are used in regional localization and can help in interpreting predictions by the SVM.	Various Datasets: Diabetic Retinopathy Dataset, Covid X-Ray, Covid CT Scan, and Alzheimer's	SVM, Quadtree, ROI	The SVM model could identify the regions of interest in mild and moderate demented images, providing a correct visual explanation. Sensitivity analysis of the SVM classifier in the model supported the visual explainability with high accuracy on all the datasets.
[54]	Study an SVM of machine learning techniques used to classify brain images. SVM will be used in this paper to analyse brain images and discover Benign Tumor and Malignant Tumor by using the MATLAB software	Benign Tumors and the others have Malignant Tumors	svm	The results of the experiments conducted showed the accuracy of the system provided for the classification of tumor types (Benign, Malignant) found in medical brain images.
[55]	This review is about the current state of SVMs developed and applied in the medical field over the years.	-	SVM-Based Models	The review highlights that the various SVM-based models have been effective in enhancing performance metrics in healthcare applications.

[56]	Proposed a new approach to classify medical images by using transfer learning methods method, namely ResNet-50, where features are reduced by an Auto Encoder (AE) and classified by A Support Vector Machine (SVM)	WBC Dataset, and X-Ray	Resnet 50	The proposed method Possess 97.3% and 99% accuracy on WBC and COVID-19 datasets, respectively, which are higher
[56]	Developed a hybrid CNN-SVM model for lung cancer classification using CT scan images.	CT Scan Image Dataset and Lung Dataset	Cnn-svm	This algorithm is evaluated, and the results indicate that our proposed CNN-SVM algorithm has succeeded in classifying lung images with 97.91% accuracy.
[57]	Hybrid Preprocessing and classification approach of CNN and SVM. CNN for Feature Extraction, while SVM for Classification, and reducing false positives.	MRI brain Dataset and Tumor classified	CNN, SVM, Sobel Edge Detection	Hibrid Model reaches an accuracy of 98.14%
[58]	Proposed a hybrid approach combining CNN for feature extraction and SVM for classification. Included threshold-based segmentation for tumor detection.	MRI Public brain Images, and Tumor	CNN, SVM	Hybrid CNN-SVM accuracy: 98.4959%. Comparisons: RELM - 94.233%, DCNN - 95%, DNN + DWA - 96%, kNN - 96.6%, CNN - 97.5%.
[59]	Aims to compare the traditional techniques of SVM and Deep Learning CNN in image classification, which involves data collection, preprocessing, implementation, and finally evaluation.	Dataset of more than 350 images (dog, pizza, dollar, sunflower, soccer ball)	SVM, CNN	SVM accuracy: 93% (small dataset), 82% (augmented dataset). CNN accuracy: 93.57%.

4.2 Comparison of AI models

This study investigates and compares the effectiveness of various approaches across different research topics, including Convolutional Neural Networks (CNN), Support Vector Machines (SVM), and a combination of the two models. To investigate the basic ideas and methods of image classification and to demonstrate the value of deep learning methods, we evaluated most of these techniques before deciding to use CNN and SVM.

By examining the fundamental ideas and methods of picture categorization and emphasizing the learning strategies involved, we investigated the article. To be able to understand and build a comprehensive understanding, we start with the CNN method, which excels in extracting image hierarchy and spatial features from raw pixel data, but realizing the advantages, some shortcomings must be addressed. CNN is reliable in data processing techniques but struggles in processing large amounts of data (Khairandish et al., 2022a). In addition to determining the model's accuracy value, this experiment gave us important insight into how combining two methods in a dataset might enhance classification outcomes. This is especially useful for complex datasets like processing photos and medical imaging. A comparison of the various models may be found below.

4.3 Medical Imaging

It is believed that clinical imaging assigns the sequence of operations that result in images of the internal body parts. The process and cycles are used to capture images of the human body for clinical applications, like identifying, evaluating, or assessing a pathology, injury, or deformity. The results of computed tomography (CT) scans are excellent examples of useful indicative imaging that promotes precise conclusions, mediation, and assessment of the harms and dysfunctions that real advisers regularly handle [38]. The use of AI in medical imaging is demonstrated in Table 2.

Table 2.
Application of AI in medical imaging.

Journal	Technique	Application
[2], [14]	CT Scan, MRI	Image interpretation for cancer detection
[15]	XAI	Imaging analysis for tumour segmentation
[16]	VGGNet	Diabetic Retinopathy screening
[17]	Deep Learning	COVID-19 detection
[17], [20]. [22]	CAD	Breast cancer diagnosis
[17]	CNN, SVM	Skin cancer diagnosis
[20]	Machine Learning	Grade of Glioblastoma prediction
[14]	Deep Learning, CMR	Hearts disease detection
[21]	VLMs	Radiology imaging interpretation

Whereas these changes might not necessarily be evident directly through conventional visual assessment by human operators, artificial intelligence can review unusual imaging modalities like cardiac magnetic resonance (CMR) and computed tomography (CT) scans for the detection of minute changes with respect to early heart disease or complications [42].

5. Discussion and Results

5.1 Key Findings and Implications

The study emphasizes how artificial intelligence (AI), namely machine learning (ML) and deep learning (DL), improves disease diagnosis, patient monitoring, and medical imaging. Among the important conclusions are the following:

a) AI-Driven Medical Imaging: CNNs significantly improve the accuracy of disease detection, particularly in tumor identification, pneumonia detection, and retinal diseases. Studies show that AI-assisted diagnosis reduces false positives and false negatives, leading to improved diagnostic precision and clinician trust.

b) Disease Diagnosis Enhancement: The combination of CNNs and SVMs enhances classification efficiency. For example, CNNs are effective in feature extraction from medical images, while SVMs improve classification, particularly in cases requiring high-dimensional data processing.
c) Patient Monitoring with AI: Wearable health monitoring devices and IoT-based solutions enhance real-time patient monitoring. AI models efficiently analyze patient vitals, enabling early detection of anomalies, thus improving personalized treatment strategies.
d) Improved Workflow Efficiency: AI integration streamlines medical processes by reducing the time required for diagnosis and supporting clinical decision-making, thereby alleviating clinician workload and enhancing patient care. These results suggest that AI could help close the gap between accurate imaging, early diagnosis, and ongoing patient monitoring, resulting in a more proactive and effective healthcare system.

5.2 Key Findings and Implications

Despite its advantages, AI in healthcare faces several challenges:

a) Data Privacy and Security: Using sensitive health data raises patient privacy issues and requires robust encryption along with healthcare compliance.
b) Interpretability of AI Models: Clinicians often struggle to trust AI decisions due to the “black box” nature of deep learning models. Enhancing model explainability through heatmaps and region-of-interest (ROI) visualization can improve adoption.
c) Data Heterogeneity: AI models must generalize well across diverse datasets. Variability in imaging techniques, demographic differences, and annotation inconsistencies can impact model performance.
d) Clinical Adoption Barriers: The integration of AI into existing healthcare infrastructure demands significant investment in computational resources, staff training, and regulatory approvals.

5.3 Comparison with Existing Literature

The result aligns with prior studies demonstrating AI’s impact on healthcare.

a) Medical Imaging Accuracy: Previous research, such as the Breast Screening-AI study, reported a 27% reduction in false positives and a 4% reduction in false negatives, reinforcing the findings of this study regarding AI’s ability to enhance diagnostic accuracy [14].
b) Hybrid AI Models: Earlier research on CNN-SVM integration confirmed the effectiveness of combining feature extraction with classification to validate the role of SVMs in improving explainability [45], [46].
c) Real-Time Monitoring: The effectiveness of AI in remote patient monitoring is corroborated by Rohmetra’s work on AI-enabled telehealth, emphasizing the role of ML in detecting anomalies in vital signs [9], [61].

This study adds to existing literature by highlighting the synergy between AI techniques in diagnostics, monitoring, and imaging, demonstrating their combined effectiveness in advancing precision medicine.

5.4 Limitation and Alternative Interpretation

While the findings are promising, certain limitations should be considered as follows:

a) Dataset Bias: The generalizability of many AI models may be limited since they are trained on particular datasets that might not be representative of other patient populations.

b) Overfitting Concerns: Some models, particularly deep CNNs, may be overfit to training data, requiring rigorous validation on external datasets.
c) Algorithmic Trade-offs: While CNNs excel in image processing, their computational demands can be prohibitive. Alternative models such as vision transformers (ViTs) could offer improved efficiency.
d) Ethical Considerations: Disparities in healthcare may be a result of bias in the AI models that are caused by unbalanced training data, and hence there must be regular model audits and fairness checks.

6. Conclusion

Artificial Intelligence (AI) has demonstrated significant potential in transforming, especially in the areas of disease diagnosis, patient monitoring, and medical imaging. The integration of AI technologies, such as Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs), has led to remarkable improvements in diagnostic accuracy, efficiency, and personalized treatment strategies. AI-driven systems have proven to be highly effective in analyzing complex medical data, enabling early detection of diseases such as cancer, cardiovascular disorders, and neurological conditions. Furthermore, AI-powered medical imaging has enhanced the precision of image analysis, reduced diagnostic errors, and improved workflow efficiency in clinical settings.

Despite these advancements, the adoption of AI in healthcare is not without problem. One of the main concerns is the lack of interpretability and transparency in AI models, which often function as "black boxes." This makes it difficult for experts in the healthcare sector to truly trust and understand the explanation behind the diagnosis provided by AI. In addition, privacy protection and data security remain crucial issues, as AI systems require a large amount of sensitive patient data, making them vulnerable to cyber threats. Ethical considerations, particularly regarding patient confidentiality and equal access to AI-based health solutions, also need to be considered to ensure that these technologies are used in a responsible manner.

The findings from this review show how important it is to create AI models that are easier to understand and implement effective data protection procedures. Future research should focus on developing AI systems that are capable of communicating with humans, where medical personnel are not replaced by AI, but rather assisted by it. This approach ensures that AI complements clinical expertise, maintaining a patient-centered and ethical healthcare framework. Moreover, efforts should be made to bridge the gap in AI adoption between high-income countries and low- and middle-income countries (LMICs), where access to advanced healthcare technologies is often limited due to infrastructure and regulatory constraints.

In conclusion, AI holds immense promises for changing the way healthcare is delivered by improving the accuracy of diagnosis, enabling direct patient monitoring, and enhancing the quality of medical imaging. However, addressing the existing challenges related to model interpretability, data security, and equitable access for successful integration of AI in clinical practice. As AI technology continues to evolve, it is expected to make an increasingly significant contribution to shaping the future of the healthcare system, ultimately improving patient outcomes and creating a more efficient healthcare system. Continued research and collaboration between technologists, healthcare providers, and policymakers will be necessary to realize the potential of AI in transforming global healthcare.

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