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EXPLORING THE ROLE OF ARTIFICIAL INTELLIGENCE IN TRANSFORMING MEDICAL IMAGING FOR DIAGNOSTICS

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Abstract: *This paper investigates the role of artificial intelligence (AI) in the medical field. This research uses descriptive qualitative methods and gathers data from related previous studies. The findings show that AI contributes to the medical field, particularly in medical imaging and diagnosis, enhancing accuracy and efficiency. AI systems, such as deep learning models and transformers, are being increasingly utilized to analyze medical images, detect abnormalities, and assist in early disease detection, such as cancer, eye diseases, and COVID-19. Transformer-based models have shown great potential in improving diagnostic accuracy by efficiently analyzing large and complex medical data. These models can capture long-range dependencies, making them ideal for handling diverse medical imaging modalities, such as X-rays, CT scans, and MRIs. Moreover, AI has proven to be highly effective in areas like retinal disease detection, lung cancer diagnosis, and infectious disease identification. Transformer models continue to demonstrate promise, with the potential to revolutionize medical diagnostics by offering faster, more precise, and personalized treatment options.*

Abstrak: Penelitian ini mengkaji peran kecerdasan buatan (AI) di bidang medis. Penelitian ini menggunakan metode kualitatif deskriptif dan mengumpulkan data dari studi sebelumnya yang relevan. Temuan menunjukkan bahwa AI berkontribusi dalam bidang medis, terutama dalam pencitraan medis dan diagnosis, dengan meningkatkan akurasi dan efisiensi. Sistem AI, seperti model deep learning dan transformer, semakin banyak digunakan untuk menganalisis citra medis, mendeteksi kelainan, dan membantu dalam deteksi dini penyakit seperti kanker, penyakit mata, dan COVID-19. Model berbasis transformer menunjukkan potensi besar dalam meningkatkan akurasi diagnosis dengan menganalisis data medis yang besar dan kompleks secara efisien. Model ini dapat menangkap dependensi jangka panjang, sehingga ideal untuk menangani berbagai jenis pencitraan medis, seperti rontgen, CT scan, dan MRI. Selain itu, AI terbukti sangat efektif dalam deteksi penyakit retina, diagnosis kanker paru-paru, dan identifikasi penyakit menular. Model transformer terus menunjukkan potensi besar, dengan kemungkinan merevolusi diagnostik medis melalui penyediaan opsi pengobatan yang lebih cepat, lebih akurat, dan lebih personal.

INTRODUCTION

In recent decades, the field of artificial intelligence (AI) has emerged as a prominent topic of discussion within the medical and image processing domains (Montero et al., 2021). At its core, AI is a computer system capable of recognizing data with the aid of pre-processed information. In the medical field, AI has the potential to facilitate rapid processing and expedite the provision of medical decision support, particularly through image processing (Montero et al., 2021). AI has transformed medical imaging by enabling faster and more accurate illness identification across various imaging tools, including X-rays, CT scans, MRIs, and ultrasounds. These AI systems analyze medical images to detect anomalies, trends, and early disease indicators that might be difficult for human doctors to identify. This technological advancement has particularly enhanced diagnostic accuracy, efficiency, and patient outcomes in disorders such as cancer, eye diseases, and COVID-19 (Al Kuwaiti et al., 2023; Wang et al., 2016; Esteva et al., 2017; Rajpurkar et al., 2017).

AI methods, such as transformers, are also frequently used in medical AI applications. Transformer-based deep learning models have made significant contributions to the field of AI in healthcare, particularly in improving diagnostic accuracy across various medical applications. Originally designed for natural language processing (NLP), these models have demonstrated an impressive ability to analyze medical data, including images, documents, and even genetic sequences, thereby guiding clinical decision-making. Their primary advantage in many diagnostic tasks is their ability to capture long-range dependencies and manage complex, high-dimensional data, which contributes to their success. One of AI's main advantages in radiology is its speed in accelerating the diagnostic process (Raffel et al., 2020). Medical image interpretations have traditionally taken time, especially in complex cases requiring detailed evaluation. AI enables images to be analyzed and processed much faster than human capability, allowing for quicker diagnoses and timely medical interventions by evaluating large volumes of images in a fraction of the time it would take a human radiologist.

In the research by Yan et al. (2022), the use of transformers for processing data in the field of radiology yielded highly accurate results. The study utilized a substantial amount of data, including 4.42 million radiology reports from the Veteran Affairs healthcare system, covering 2.17 million unique patients. The findings of this study highlight the effectiveness of artificial intelligence in handling large volumes of data. Other methods, such as Generative Adversarial Networks (GANs), are also frequently used in medical image processing. Goodfellow et al. (2014) initially proposed GANs as a means to generate a target image in the absence of a specific input image. This pioneering work was later refined into Conditional Generative Adversarial Networks (cGANs), marking a significant advancement in the field. A key feature of cGANs is their incorporation of input images, which distinguishes them from GANs. In the study by Cao et al. (2020), a method known as Auto-GAN was developed. This approach utilizes multi-modal image sources from various domains, combined with a self-representation of the target domain, to effectively and jointly control a better decoder on a layer-by-layer basis. Currently, AI and machine learning models have achieved significant results, often performing tasks with accuracy and precision that closely match, or even surpass, professional human decisions (Montero et al., 2021).

Considering the significant role of AI, the present study will investigate its application in medical imaging and diagnosis. This research aims to explore how AI is a powerful tool in assisting people within the medical industry.

METHOD

The research method employed in this study involves the collection of research papers from 2020 to 2025 using the Google Scholar Database and the Publish or Perish (PoP) tool. Following the meticulous selection process, 200 relevant papers were identified. These documents were subsequently stored in the Research Information System (RIS) format (Cahyo et al., 2025). The subsequent stage involves the utilization of VOSViewer to elucidate the distribution of data and research gaps that have been identified in preceding studies. The results of this mapping process will yield several studies based on clusters that are automatically grouped by VOSViewer. In this study, an analysis will be conducted based on titles and abstracts to ascertain the distribution of both.

As illustrated in Figure 1, the distribution of data in the titles is represented. The figure elucidates the interrelationships between topics in literature or research related to "artificial intelligence" (AI) in the medical field. The size of the nodes, particularly those labeled "artificial intelligence," "application," and "diagnosis," signifies their centrality or frequency within the network. These prominent nodes are distinguished by their larger size and dominant red color, which serves as a visual cue for their significance. The figure reveals the presence of three primary clusters, each distinguished by a distinct color: red signifies general AI and its applications, blue denotes diagnosis and deep learning, and green specifies more specific topics related to radiology and advanced technologies such as "transformers" and "medical image segmentation." The relationships between these concepts are illustrated by edges, which represent the strength or frequency of the relationship between the topics. Some topics function as bridges between different clusters, such as "medical imaging," which connects the blue and green communities. This visualization illustrates how AI is integrated into various aspects of medical diagnosis and technology.

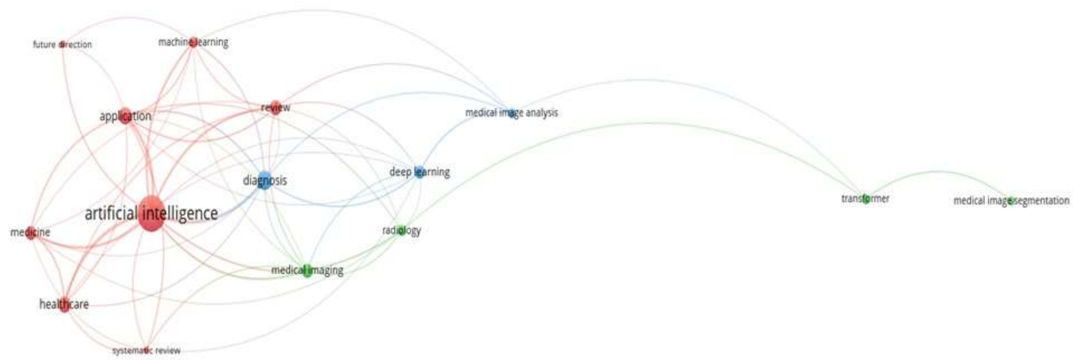

Figure 1. Titles Network Visualization

As illustrated in Figure 2, the distribution of abstracts is characterized by a specific configuration. This network visualization of the abstract distribution reveals a more intricate and structured topic architecture in research concerning "artificial intelligence" (AI) within the health and medical domain. The utilization of distinct colors to denote various themes within the abstract distribution further enhances the comprehensibility of the network. Specifically, four distinct clusters are identified: blue, green, red, and yellow. The blue cluster, in particular, emphasizes the interconnection between AI and its applications in the healthcare system, encompassing subjects such as "artificial intelligence," "machine learning," "medicine," and "healthcare." The green cluster encompasses subjects such as "diagnosis," "disease," "detection," and "diagnostic imaging," illustrating the application of AI in disease detection and diagnosis.

Conversely, the red cluster pertains to technical aspects such as "medical image analysis," "transformers," "medical image segmentation," and "artificial neural networks," signifying a concentration on medical image processing and analysis employing sophisticated AI technologies. Additionally, a yellow cluster has been identified, which connects the topics of "medical imaging," "deep learning," and "research." This cluster serves as a link between the diagnostic cluster and technical applications. This network underscores the multifaceted utilization of AI in the medical realm, ranging from its general implementation to its application in highly specialized domains such as image-based diagnosis and advanced machine learning technologies.

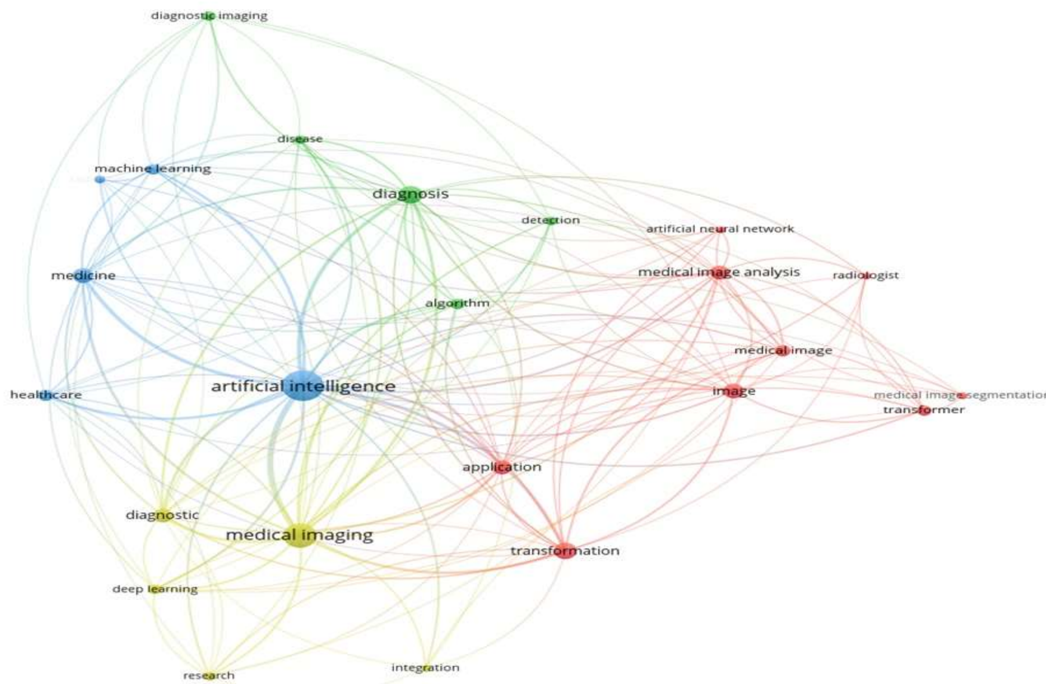

Figure 2. Abstracts Network Visualization

In general, both visualizations confirm that AI research in the medical field is developing in two main directions: (1) the use of AI to improve diagnosis and rapid clinical decision-making, and (2) the development of AI technologies to process and analyze medical data, particularly medical images. The network also shows the integration between technical research and clinical applications, utilizing technologies such as (a) medical image analysis: generative adversarial networks (GANs), convolutional neural networks, artificial neural networks, (b) segmentation, (c) transformers, and (d) deep learning.

RESULT AND DISCUSSION

AI Tools in Medical Image Analysis Results

AI has transformed medical imaging by allowing faster and more accurate illness identification than many imaging tools. Cancer detection is among the most powerful uses of artificial intelligence in medical picture analysis. Deep learning models are taught to identify trends in medical imaging that point to the existence of malignancies or aberrant development. AI models can help detect early-stage tumors—even before they show clinically—in imaging tools, including mammography, CT scans, and MRI

(Raghavendra et al., 2023; Nassif et al., 2022). AI systems, for instance, examine mammograms in search of microcalcifications—small calcium deposits—which can indicate early stages of breast cancer. These instruments help to improve early diagnostic and treatment results by pointing up minor irregularities the human eye would overlook (Houssami et al., 2019; Watanabe et al., 2019). AI algorithms, which use CT scans and chest X-rays, also help diagnose lung cancer. They can spot nodules or abnormalities in lung tissue that might point to cancer, therefore facilitating quick intervention. Apart from early identification, AI technologies can assist in tumor size, location, and stage assessment—all of which are vital for treatment planning and guide the choice of course of action, whether radiation, chemotherapy, or surgery is the most appropriate one (Alam et al., 2024; Watanabe et al., 2019).

According to Agrawal et al. (2024), Demirchan et al. (2025), and Gharge et al. (2024), AI has shown considerable potential, especially in the detection of retinal illnesses that, if left untreated late on, might cause blindness. Fundus imaging or optical coherence tomography (OCT) scans of the eye allow one to frequently diagnose diseases such as diabetic retinopathy, age-related macular degeneration (AMD), and glaucoma. AI systems can examine retinal images, for instance, to identify symptoms of diabetic retinopathy—a typical diabetic disorder damaging the retinal blood vessels. AI tools can detect early-stage retinal abnormalities such as hemorrhages or microaneurysms, enabling earlier intervention and avoiding vision loss (Grzybowski et al., 2020; Vujosevic et al., 2020). Likewise, AI-powered techniques are used to identify glaucoma, in which rising eye pressure might harm the optic nerve, or macular degeneration, in which alterations in the macula might cause central vision loss. AI models may process large volumes of retinal images, making them useful in screening campaigns aiming at early, treatable stage diagnosis of many disorders (Silva et al., 2024).

Al Kuwaiti et al. (2023) state that the COVID-19 epidemic underlined the critical role AI may play in identifying infectious diseases, mainly through the analysis of chest X-rays and CT scans. Early in the epidemic, ground-glass opacities and consolidation—commonly observed in COVID-19 patients—were developed in AI models to identify indicators of COVID-19-related lung abnormalities. In circumstances of limited or delayed access to PCR testing, AI algorithms have been included in hospital imaging systems to help radiologists rapidly identify possible COVID-19 cases. Based on the unique patterns seen in the lungs, artificial intelligence can separate COVID-19 pneumonia from other forms of pneumonia, including bacterial or viral pneumonia, by examining CT scans (Lin et al., 2021). Not only managing patient care, but also allocating resources depends on this quick diagnosis, especially in highly sought-after healthcare environments at the peak of infection.

Integrating AI systems into clinical practice presents difficulties, even with their great uses. It is essential to ensure AI models' correctness, dependability, and generalizability over several patient populations and imaging equipment. Furthermore, healthcare providers—who have to know the reasoning behind AI-generated diagnosis—must find AI technologies open and understandable. As artificial intelligence develops, its influence in medical imaging will probably grow to incorporate more diseases, more sophisticated imaging methods, and better integration with other medical technology, producing more advanced and efficient healthcare services.

Transformer-Based Deep Learning Models in Improving Diagnostic Accuracy

Tahap Introduced in the publication "Attention Is All You Need" by Vaswani et al. in 2017, transformer models replaced conventional recurrent neural networks (RNNs) and convolutional neural networks (CNNs) with a design depending on self-attention mechanisms, hence transforming deep learning. Transformers are able to effectively and without constraints of past models process both types of data, unlike CNNs that perform well for spatial data (such as photos) or RNNs that shine with sequential data (like text). Key for accurate diagnosis, they allow themselves to concentrate on pertinent elements in medical imaging or patient histories by using attention mechanisms to balance the relevance of various sections of the incoming material.

Transformer-based models have shown potential in medical imaging in enhancing diagnostic accuracy over many modalities including X-rays, CT scans, MRIs, and ultrasonic pictures (Rane, 2023). Convolutional neural networks (CNNs) have long been the preferred deep learning design for image-based tasks (Iqbal et al., 2023). Yet, transformers are catching long-range dependencies in images, which CNNs could overlook, thus they are taking front stage (Vafaeezadeh et al., 2024). Transformers analyze both local and global aspects, hence they process the whole image at once (Shamshad et al., (2023). This global background is crucial in spotting minor anomalies and trends (Baidya & Jeong, 2023). Transformers, for instance, could assist with identifying tiny tumors or abnormalities in cancer detection that might be missed on regular exams. This detection is critical early in cancer when a missed diagnosis can drastically affect patient outcomes (Chung et al., 2024).

Transformers-based artificial intelligence algorithms can examine CT scans in lung cancer screening to find minor nodules or anomalies suggesting possible malignancy (Said et al., 2023). Transformers improve the sensitivity and specificity of the diagnosis by allowing one to concentrate on the most pertinent areas of the image and by their adaptability in handling several imaging modalities (Maheriya et al., 2025; Fu et al., 2025). Gupta et al. (2024) created a Vision Transformer (ViT-Base) model with transformers as the basic model. The model's functionality involves the intersection of the image and the extraction of spatial features. ViT architecture has demonstrated a notable capacity for adapting effectively to different model sizes while maintaining high data recognition (Steiner et al., 2021). The architectural design of the model is depicted in Figure 3.

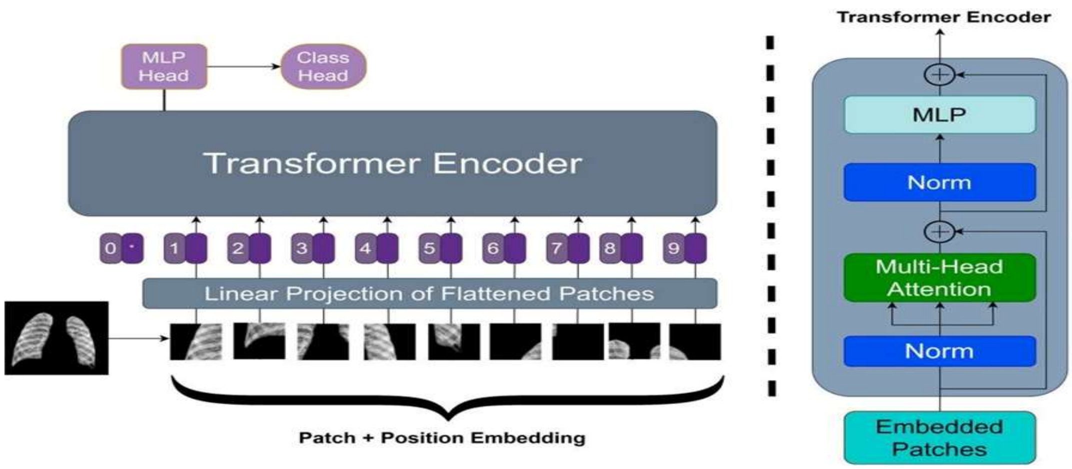

Figure 3. ViT Architecture (Gupta et al., 2024)

The ViT model has evolved into MobileViT, a hybrid model that integrates the transformer architecture with Convolutional Neural Networks (CNNs). MobileViT was specifically designed for mobile devices, addressing the need for computational efficiency without sacrificing performance. By combining the power of transformers for capturing long-range dependencies with CNNs for local feature extraction, MobileViT reduces the computational burden typically seen in traditional transformer models (Wang et al., 2024). This optimization is particularly beneficial for mobile applications, where computational resources are often limited. MobileViT enhances the processing speed and accuracy of image analysis tasks, making it well-suited for real-time medical imaging, object recognition, and other resource-constrained environments. The architectural model of MobileViT can be seen in Figure 4.

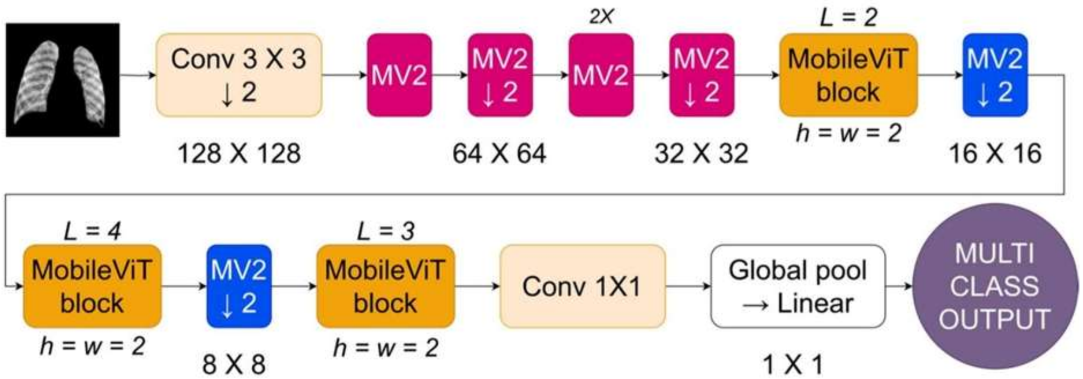

Figure 4. MobileViT Architecture (Gupta et al., 2024)

Transformer models have also demonstrated their effectiveness in pathology and genetics (Santos et al., 2023). Large databases, including patient medical histories and genetic sequences, must be analyzed in these fields to identify trends suggesting illness risk or prognosis (Dash et al., 2019). Transformers are well-suited for this task as they can effectively analyze the sequence of genetic data and related medical information, making them ideal for handling complex, high-dimensional data. For example, in genomics, transformer models can examine genetic sequences to identify mutations associated with diseases, such as cancer, and predict how these changes may affect the progression of illness (Choi & Lee, 2023). By combining genomic data with clinical information, transformers can help doctors more accurately predict a patient's condition and potential treatment options.

Natural language processing (NLP) of clinical documents is another area where transformer models improve diagnostic accuracy (Vasani et al., 2024). Manually extracting relevant information from medical records, patient histories, and doctors' notes can be challenging. However, transformer-based NLP models like BERT (Bidirectional Encoder Representations from Transformers) and GPT (Generative Pretrained Transformer) make processing large volumes of unstructured text data possible (Santos et al., 2023). Transformers can, for example, be used to identify risk factors, extract pertinent data from medical records, or even detect symptoms of diseases mentioned in a patient's history but not clearly recognized (Dash et al., 2019). This allows healthcare providers to quickly sift through large amounts of patient data, ensuring that critical diagnostic clues are not overlooked.

Clinical decision support systems (CDSS) assist healthcare professionals in diagnosing and treating patients; transformer-based models are crucial for their success

(Teufel & Binder, 2021). Transformers can generate highly accurate predictions and treatment recommendations by integrating data from medical images, clinical texts, lab reports, and sensor data (He et al., 2023). For instance, a transformer model could combine a patient's medical history with X-ray images and lab results to predict the likelihood of a particular condition, such as pneumonia or heart failure (Li et al., 2024). This comprehensive approach enables context-aware predictions that consider all patient health aspects, leading to more personalized and accurate diagnoses. Additionally, as more data becomes available, these models continue to improve, allowing diagnostic recommendations to evolve alongside medical knowledge.

Despite the great potential of transformer-based deep learning models to enhance diagnostic accuracy, some challenges remain. One major obstacle is the need for large, high-quality datasets to train these models correctly (Singh & Mahmood, 2021). In healthcare, access to such data is often limited due to privacy concerns and regulations, such as HIPAA (Health Insurance Portability and Accountability Act) (Perle et al., 2024). Moreover, while transformers excel at identifying trends in data, their interpretability is still a concern. Healthcare professionals must understand why a model generates a particular diagnosis (Lai, 2024), especially when using complex transformer-based systems.

Another challenge is integrating transformer-based AI models into existing healthcare technologies, such as electronic health records (EHRs) (Evan, 2016) and ensuring seamless operation within healthcare workflows. Despite these challenges, the future of transformer-based models in medical diagnosis looks promising. As more medical data becomes available and these models continue to evolve, they will likely become a natural part of clinical decision-making, offering more accurate, personalized, and timely diagnoses, ultimately improving patient outcomes.

Transformer-based deep learning models have the potential to revolutionize medical diagnostics by improving accuracy, efficiency, and clinical decision-making (Bhandari et al., 2023). Whether applied to medical imaging, genomics, or clinical text analysis, these models enhance healthcare providers' ability to diagnose diseases more precisely and earlier. As technology advances, transformer models are expected to play an even more significant role in shaping the future of medical diagnostics, offering hope for better patient care and outcomes worldwide.

CONCLUSION

In conclusion, artificial intelligence (AI) has significantly transformed the field of medical diagnostics, particularly in medical imaging and data analysis. With advancements in deep learning models like transformers, AI enhances diagnostic accuracy, efficiency, and the speed at which medical conditions can be detected. Medical imaging tools such as CT scans, MRIs, and X-rays have become more accurate in identifying anomalies and early signs of diseases like cancer and eye conditions, which were previously difficult for humans to detect. AI is also crucial in speeding up the diagnostic process, allowing healthcare providers to make timely decisions, thus improving patient outcomes.

Transformer-based deep learning models have emerged as powerful tools in healthcare, especially in medical image analysis and genomics. These models can handle complex, high-dimensional data by capturing long-range dependencies, making them particularly effective in analyzing medical images and patient records. Transformers offer more accurate and personalized diagnoses by integrating different types of data, such as genetic sequences and medical histories. Moreover, AI technologies like NLP models based on transformers are enhancing the analysis of clinical documents, allowing healthcare professionals to identify crucial information that may otherwise be overlooked quickly.

Despite AI's impressive advancements in medical diagnostics, there are still challenges to overcome. One significant obstacle is the need for large, high-quality datasets, which are often restricted due to privacy concerns and regulations like HIPAA. Additionally, the interpretability of transformer models remains an issue, as healthcare providers must understand how AI models arrive at specific conclusions. Another challenge is the integration of these models into existing healthcare systems, ensuring seamless collaboration with current technologies like electronic health records (EHRs).

The role of transformer-based models in medical diagnostics is expected to grow. As more data becomes available and AI technologies evolve, these models will become more integrated into clinical decision-making, offering more accurate and personalized diagnostic capabilities. The continuous improvement of these models promises to revolutionize medical diagnostics, ultimately leading to better patient care and more effective treatments. AI's role in healthcare, mainly through advanced models like transformers, is poised to shape the future of medical diagnosis and patient outcomes worldwide.

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