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X-Ray Vision: AI-Driven Detection of Disease - A Survey on Deep Learning-Based Pneumonia and Brain Tumour Detection

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Abstract: AI has been integrated in every sector. AI in health sector plays major role to boost the work efficiency of doctor's, radiologists, and generalist. AI has been gaming changing method for automating disease detection. This survey shows how using Deep Learning can help the Radiologists to ease their work. This survey uses convolutional neural networks (CNNs) to detect brain tumour and pneumonia. We present a partially implemented prototype system named "X-Ray Vision' that combines image classification models for brain tumour detection and pneumonia. This survey also underlines current challenges, potential improvements, and deployment through a web-based interface.
Keywords: X-Ray Vision, Disease Detection, Brain Tumour, Pneumonia, Deep Learning, Convolutional Neural Network (CNNs), AI in healthcare, Medical Imaging

I. INTRODUCTION

Automation in disease detection plays a crucial role in assisting radiologists. Traditionally, radiologists manually examine medical images, which is a time-consuming process and often prone to human error. To accelerate this process and improve diagnostic accuracy, deep learning-based AI models are now being used to automate medical image analysis. These models also help reduce the workload of radiologists.

Artificial Intelligence (AI) and Deep Learning in disease detection primarily rely on Convolutional Neural Networks (CNNs), which automatically learn complex and detailed visual features from medical images. This survey presents an overview of our partially implemented prototype, "X-Ray Vision," which currently focuses on detecting brain tumors and pneumonia. Both of these are potentially fatal illnesses that require early and accurate diagnosis. To address this challenge, "X-Ray Vision" not only detects diseases but also stores patient records in a web-based database system. In case any scanned image or patient record is lost, the system provides simple retrieval and search functionalities through its integrated web interface.

So how does AI achieve such accurate detection from scanned images? The model is trained using large, labeled datasets. One set of images contains examples of disease (for instance, scans showing brain tumors), while another set includes normal images without any abnormalities. Through this training process, the model learns to differentiate between healthy and diseased scans effectively.

CNNs are particularly powerful in medical imaging because they can learn directly from raw pixel data rather than relying on predefined rules or manual feature extraction. When analyzing scan images, the network's early layers detect simple patterns such as edges and lines, while deeper layers capture more meaningful structures like tissues, organs, or tumor boundaries. This hierarchical learning enables CNNs to perform precise and consistent medical diagnoses.

By training the model with a large dataset and testing it repeatedly, its accuracy approaches radiologist-level performance as reported in prior studies. Deploying this system also allows all scanned images to be stored digitally within the database, reducing the need for manual documentation. Even if physical copies are lost, the digital records remain accessible. Efficient record management, along with reliable disease prediction, helps radiologists reduce their workload and focus on patient care.

In the future, integrating additional disease detection models into this system can further automate healthcare workflows. Such advancements will enable doctors to work more efficiently with the assistance of intelligent systems. Artificial Intelligence and Deep Learning are set to bring a revolutionary transformation to the healthcare field.

II. RELATED WORK & SHORTCOMINGS

1) Kermany et al. (2018) – Deep Learning for Pneumonia Detection: One of the first large-scale CNN models made for identifying pneumonia from chest X-ray images was created by Kermany and associates.

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Their model used a large labelled dataset and transfer learning to achieve high diagnostic accuracy. The only issue it had was the system required lots of computational power. The system was not compatible for real time performance and it was not built into a clinically deployable application

2) Masoud Nickparvar (2021) – Brain Tumour MRI Dataset and CNN Implementation (Kaggle): A structured MRI dataset of brain tumours and multiple CNN-based tumour classification implementations were made available by Nickparvar. Medical AI models are now frequently trained and validated using this dataset. The drawback was the implementations were experimental and did not have validation using actual hospital data or a variety of MRI scanners. The CNN models were not integrated into a single web or diagnostic system; instead, they were trained separately.
3) Pereira et al. (2016) – Brain Tumour Segmentation Using Deep CNNs Deep CNNs were used by Pereira and associates to segment brain tumours in MRI images pixel-by-pixel. When compared to traditional segmentation algorithms, their work increased the accuracy of boundary detection. The limitation were segmentation models needed a lot of manual annotation and took a long time to train. When the dataset size was small, the method also suffered from overfitting.

III. LITERATURE SURVEY

Over the past decade, the use of deep learning in medical imaging has rapidly increased, offering new possibilities for early disease detection and clinical support. Among various techniques, Convolutional Neural Networks (CNNs) have gained exceptional attention for their ability to learn complex visual patterns directly from medical scans. Many researchers have experimented with CNN-based models to classify and diagnose diseases such as pneumonia and brain tumors. The following section reviews some of the most influential studies that have shaped this area of research.

In 2018, Kermany et al**.** carried out one of the earliest large-scale experiments using CNNs for pneumonia detection through chest X-ray images. Their model achieved impressive accuracy and was able to distinguish between healthy and infected lungs effectively. This study highlighted the potential of deep learning in supporting radiologists. However, their approach required heavy computational power and was not suitable for real-time or low-resource medical environments.

Similarly, Rajpurkar et al. (2017) developed *CheXNet*, a very deep 121-layer DenseNet model trained on more than one hundred thousand chest X-ray images. It reached radiologist-level accuracy, proving that neural networks could be trusted for diagnostic tasks. Yet, the model's extreme depth made it complex and resource-intensive. It was also difficult to interpret, which made medical professionals hesitant to rely solely on its predictions.

For brain tumor diagnosis, Masoud Nickparvar (2021) introduced a public *Brain Tumor MRI Dataset* on Kaggle, along with several CNN-based classification models. These implementations showed how AI could classify brain scans into normal and abnormal categories. The dataset became widely used for research and training purposes. However, these experiments remained mostly academic — they were not validated in real hospital conditions and lacked integration with real-time applications or patient data systems.

Earlier, Pereira et al. (2016) focused on brain tumor segmentation using deep CNNs. Their model improved the precision of tumor boundary detection compared to conventional methods, showing how CNNs could capture fine spatial details in MRI images. The main limitation was the need for manually annotated datasets and the long training time required for each model. Overfitting also became a concern when smaller datasets were used.

Later, Abdelhafiz et al. (2019) explored transfer learning with 3D CNNs for multi-class brain tumor classification. By using pre-trained networks, they improved overall accuracy and reduced the amount of data needed for training. Still, the approach required large memory capacity and complex fine-tuning, which limited its use in real-time healthcare environments. Moreover, their study focused only on tumor classification and did not include tools for clinical deployment.

From this review, it is clear that deep learning — particularly CNN architectures — has shown remarkable results in medical image-based disease detection. However, most previous studies share a few common limitations. Many were restricted to a single disease category, demanded high-end computational setups, and lacked interpretability or user-friendly deployment. Few offered a complete solution that combined automated detection with patient data management.

The proposed "X-Ray Vision" system aims to bridge these gaps. Unlike previous works, it combines pneumonia and brain tumor detection within a single framework while providing a practical web interface for radiologists. The inclusion of database storage and easy record retrieval makes it suitable for real-world medical use. In this way, the system not only improves diagnostic automation but also ensures accessibility and continuity of patient records — something most earlier models overlooked.

IV. PROPOSED SYSTEM

The traditional techniques used in disease detection faced several limitations. Many existing models required extensive preprocessing time, while others lacked the capability for real-time analysis. Some systems demanded high computational power or focused solely on model design without considering deployment or usability. In short, no single research provided a complete, end-to-end solution that could perform both accurate diagnosis and practical data management.

The proposed system, named "X-Ray Vision," aims to overcome these challenges by integrating all stages of medical image analysis — from model training and evaluation to real-time deployment and web-based accessibility. The system focuses on building reliable AI models using large, well-structured datasets while also ensuring that the output can be easily used by radiologists through a clean and intuitive web interface.

One of the key strengths of "X-Ray Vision" lies in its web features. The application allows users to upload medical images, perform disease detection, view prediction results, and store reports directly in a connected database. It also provides easy search and retrieval options for patient records, along with a simple, visually organized dashboard for result interpretation. This makes the system practical and efficient for everyday use in healthcare environments.

The proposed system consists of two deep learning models, each trained for a specific medical condition:

1) Brain Tumor Detection Model – trained using MRI images.

2) Pneumonia Detection Model – trained using chest X-ray images.

Both models are integrated into the same web platform, enabling radiologists to analyze different types of medical scans using a single application. Once the image is uploaded, the system automatically identifies the appropriate model, performs the prediction, and stores the corresponding result in the database. This combination of deep learning and web-based record management offers a complete and scalable solution that enhances the efficiency and reliability of medical diagnosis.

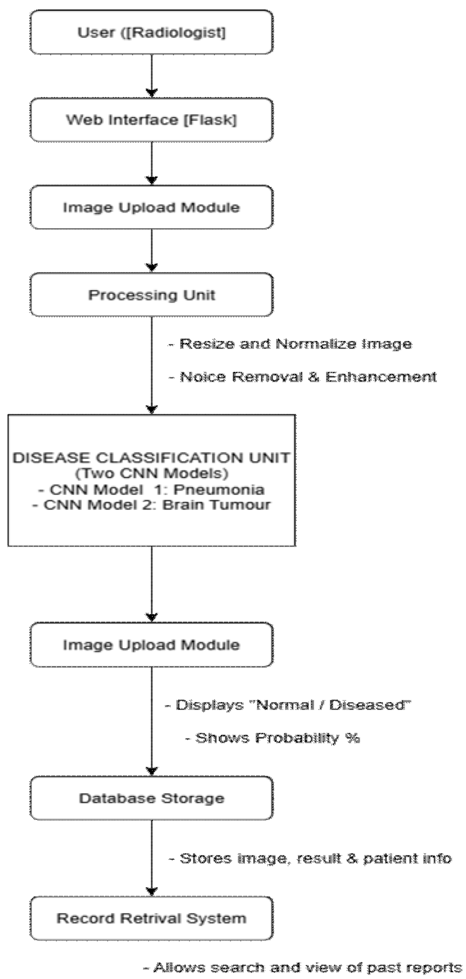

Fig. 1 Model System Architectural Flow

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The system architecture of the proposed "X-Ray Vision" model is designed to automate the process of disease detection and patient record management in an efficient and user-friendly way. The overall workflow begins when the radiologist or user uploads an image—either a chest X-ray or a brain MRI—through the web interface. This interface, built using the Flask framework, serves as the main interaction point between the user and the AI models. The pre-processing unit receives the uploaded image and performs a number of enhancement operations on it. To guarantee consistency throughout the dataset, the image is normalized, resized to a fixed dimension, and, if necessary, converted to grayscale. This step lowers training and prediction errors and improves the accuracy of the CNN models' feature recognition. The pre-processing module makes sure that only pertinent medical features are kept in images with background noise or erratic lighting.

The system automatically routes the image to the relevant disease classification module following pre-processing. This module includes two distinct CNN-based models, one specifically designed to detect brain tumour's from MRI images and the other specifically designed to detect pneumonia from chest X-rays. The corresponding model carries out feature extraction and classification based on the type of image. The CNN model gradually learns to recognize visual traits that differentiate healthy scans from diseased ones by processing the input through several layers of convolution and pooling. The output layer then predicts the probability score of the outcome as well as whether the image is "Normal" or "Diseased."

After prediction generation, the outcome is sent to the web interface's output display module. The classification result and its probability value are visible to the radiologist. Together with the uploaded image and patient information, all results are also kept in a database to make the system more useful in a medical setting. This guarantees that diagnostic information is always available and is never lost.

An essential component of the architecture is the database storage and retrieval system. Users can review patient histories, compare previous reports, and search for previous scans. This feature helps keep a digital archive of all diagnostic data and does away with the need for manual recordkeeping. Furthermore, it offers a methodical basis for upcoming studies and model enhancements.

This complete flow of architecture shows the interaction between user and model. It connects from input data o model to output to the webpage. This not only accelerates the disease detection process but also improves accuracy, reduces human error, and minimizes the workload of radiologists by automating repetitive tasks.

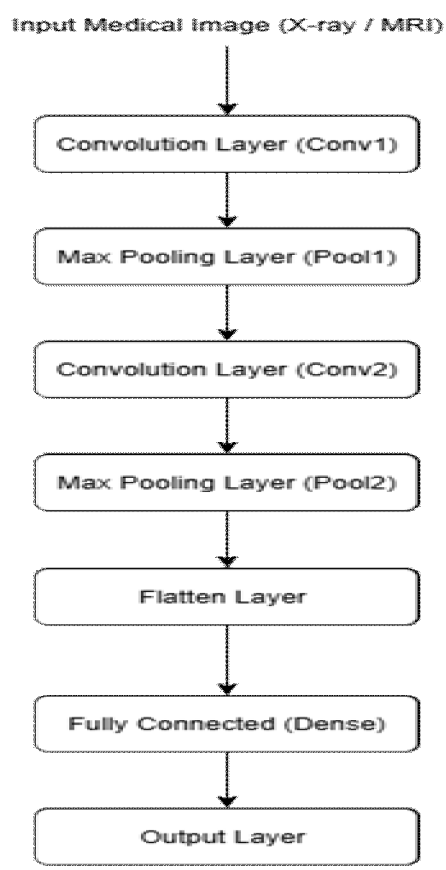

Fig. 2 CNN Model Architectural Diagram

A Convolutional Neural Network (CNN), a deep learning model specifically created for image recognition and analysis, is the foundation of the "X-Ray Vision" system. The ability of CNNs to automatically learn and extract visual patterns that differentiate between healthy and diseased conditions has made them extremely effective for processing medical images. CNNs learn these features directly from the data during training, in contrast to traditional algorithms that need feature selection to be done by hand. CNN architecture is used to build the Brain Tumour Detection Model and the Pneumonia Detection Model in the suggested system. An X-ray or an MRI image is fed into each model, which then processes it through a series of layers, each of which learns more intricate patterns.

The input layer, the network's initial stage, takes in the medical image and transforms it into pixel values. To ensure consistency throughout the dataset, the image is resized to a fixed dimension, such as 128 x 128 pixels. This guarantees that the model's input size is constant.

Convolution Layers, which are in charge of feature extraction, are the next step. These layers employ a number of filters to identify the image's edges, textures, and other minute details. The network starts to identify higher-level characteristics, like patterns and shapes that indicate diseased areas, as it gets deeper. The Rectified Linear Unit (ReLU) activation function, which adds non-linearity and aids in the model's learning of intricate relationships, comes after each convolution operation.

Following convolution, the data is passed through pooling layers, which preserve the most significant features while reducing the spatial dimensions. In addition to reducing computational expense, this step aids the model in concentrating on the most prevalent patterns. The CNN effectively captures both fine and global image details thanks to the combination of convolution and pooling layers.

The Flatten Layer prepares the data for classification by flattening the key features into a single vector after they have been extracted. These features are then interpreted and mapped to the final output classes by the Fully Connected (Dense) Layers. The output layer, the final layer in the model, classifies the image as either normal or diseased using a sigmoid activation function. This binary output is easy to understand and appropriate for medical diagnosis.

During training, both CNN models are optimized using datasets collected from Kaggle: the *Chest X-ray Pneumonia Dataset* and the Brain Tumour MRI Dataset. Various data augmentation techniques—such as rotation, flipping, and zooming were applied to improve model generalization and reduce overfitting. The models were trained for multiple epochs until stable accuracy and loss values were achieved.

V. RESULT

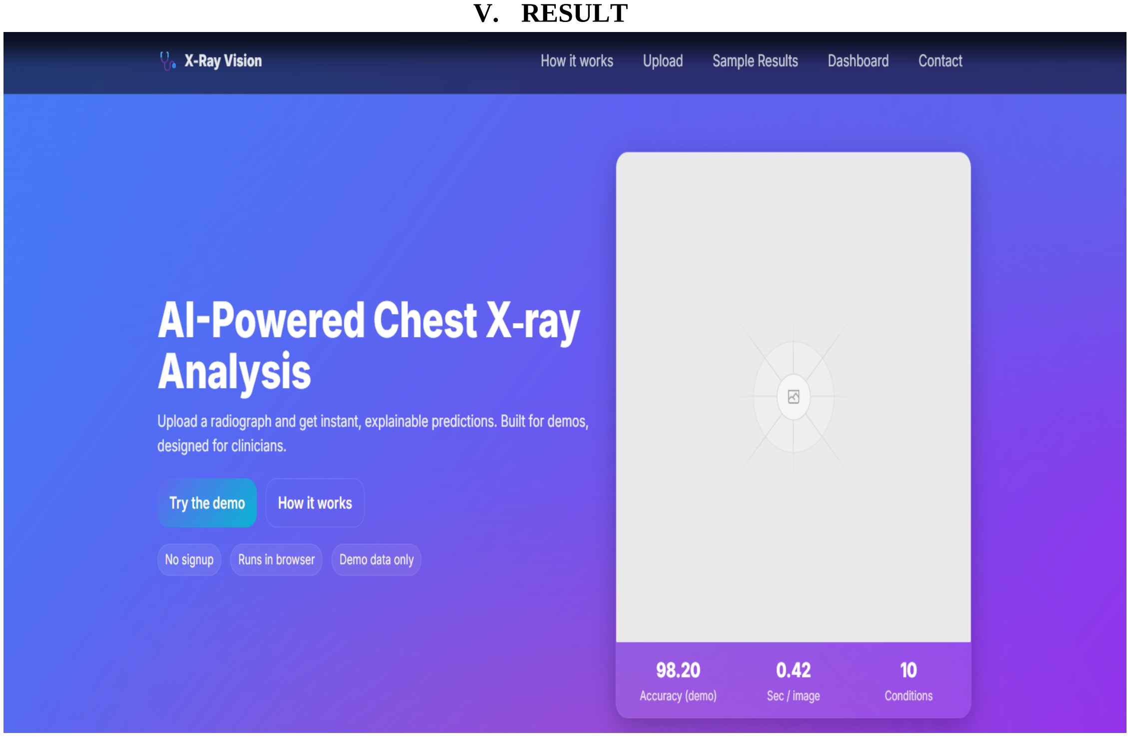

Fig. 3 X-Ray Vision Webpage Dashboard

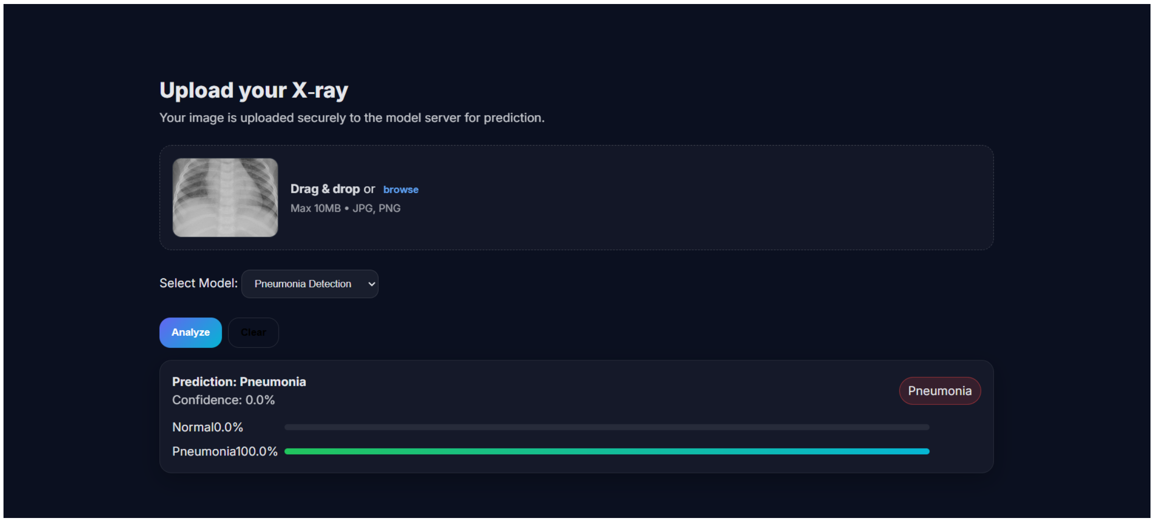

Fig. 4 Pneumonia Model Detection Test

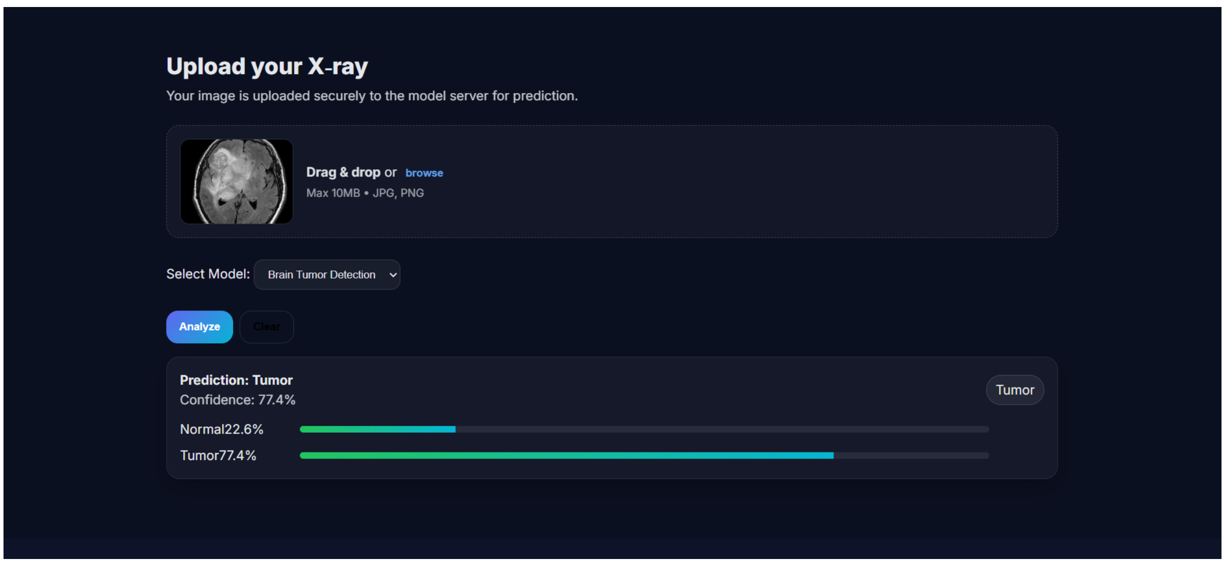

Fig. 5 Brain Tumour Model Detection Test

VI. CONCLUSION & FUTURE SCOPE

Overall, this survey demonstrates how well deep learning can identify brain tumours and pneumonia from medical images. Our partial implementation shows that lightweight CNN architectures can still be used for web deployment and still achieve dependable accuracy. To improve interpretability and reliability, future research will concentrate on clinical validation, explainable AI integration, and dataset augmentation.

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