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INTEGRATING OMNICHANNEL SERVICES AND PREDICTING DISEASES USING X RAY IMAGES IN DEEP LEARNING

Dr.Ramachandiran.R
Professor
Department Of Computer Science And Engineering
Sri Manakula Vinayagar Engineering College
Puducherry, India

Mr.Mugilan J
Department Of Computer Science And Engineering
Sri Manakula Vinayagar Engineering College
Puducherry,India

Mr.Sudharsan S
Department Of Computer Science And Engineering
Sri Manakula Vinayagar Engineering College
Puducherry, India

Mr.Aswin J
Department Of Computer Science And Engineering
Sri Manakula Vinayagar Engineering College
Puducherry, India

Abstract**—** Omnichannel interaction services in healthcare enable seamless access through platforms like mobile apps, online portals, and telemedicine, enhancing personalized patient experiences. The COVID-19 pandemic brought focus to their relevance in making continuous care possible even when constrained. Despite advancements in data storage, real-time analysis for disease prediction and early diagnosis remains a challenge. Traditional methods often fall short in meeting the speed and accuracy demands of critical care. To address this, an AI-driven system using a customized Convolutional Neural Network (CNN) along with ResNet101 is used for disease prediction and early detection of diseases such as tuberculosis, COVID-19, and pneumonia. Customized CNN will be used for extracting relevant features from X-ray images, and ResNet101, a deep residual network, will enhance the model's ability to identify complex patterns with high accuracy. This hybrid approach enhances diagnostic accuracy and decision-making while optimizing healthcare workflows to improve patient outcomes.

Keywords-Lung Disease classification,Chest X-Ray and CT scan images,Convolutional Neural Network,VGG19 architecture,Classification System

I INTRODUCTION

The pandemic's impact on HSCs brought to light the inadequacies of traditional disruption planning, mitigation, and recovery procedures. Most healthcare organizations found their existing strategies ineffective in coping with the scale and scope of COVID-19-related disruptions. As a result, many healthcare providers had to rethink their operations and adopt new approaches to survive and adapt. The old equilibrium, which was centered around conventional methods of operation, was no longer viable. This transformation in the healthcare sector, spurred by the pandemic, is reshaping the way services are delivered managed, with a significant shift toward more dynamic and responsive systems.

Omnichannel systems are meant to deliver seamless, interruption-free services to the consumers. An important aspect of such systems is the option of a patient switching channels of communication and not having to input his information again. A patient might be in the process of filling a health form online or through an app, when they need support in real-time. With an omnichannel system, the healthcare staff can access pre-filled data to provide real-time assistance in order to streamline the process and increase patient satisfaction. This seamless integration of various communication channels is key to improving the user experience as well as efficiency in healthcare services.

The pandemic has spurred renewed interest in developing strategies to strengthen supply chains, particularly in healthcare, where the impact of disruptions extends beyond financial losses to critical concerns like patient safety. Despite the growing interest in supply chain resilience, limited attention has been given to developing specific strategies for HSC.This requires conducting research to understand the specific challenges that healthcare supply chains face and to identify the solutions that can improve its ability to adapt and recover during crises. Adopting omnichannel systems could play a crucial role in building resilience, ensuring that HSCs can continue to function effectively even during times of disruption.

II RELATED WORK

[1] Farheen Naz 2023:

The study focuses on the resilience factors within the healthcare supply chain (HSC) and aims to build the foundation for an Omni-Channel Healthcare Supply Chain Resiliency (OHSCR) model. Despite the growing importance of resilient healthcare systems, very little research has been conducted in terms of specific factors that are contributors to the resilience of HSCs, especially with respect to omnichannel approaches. In the first phase, the researchers conducted a detailed comprehensive literature review, laying the groundwork for a deeper exploration of the issue. In the second phase, the researchers employed machine learning techniques, particularly K-means clustering, to develop a framework for the futuristic blocks of OHSCR. K-means clustering helped categorize the identified resilience factors into distinct groups, making it easier to analyze and prioritize these factors for the future development of resilient and adaptive healthcare supply chains.

[2] Carlos Alves 2023:

The rapid growth of technology through the Internet of Things (IoT) has gained widespread penetration and transformed the healthcare sector significantly in terms of improving business quality, providing an easy and seamless customer experience, and maximizing the profit potential. However, one of the imperative products emerging from such technological migration is omnichannel services, that is, through both online and offline means, bringing real-time information and services to customers. This integration promotes more engagement and access to healthcare services. Healthcare wearable devices, which are the core part of the IoT ecosystem, have become essential in connecting healthcare providers with patients, thus playing a pivotal role in the omnichannel environment. This study seeks to address these gaps by offering an integrated approach that combines traditional statistical methods with machine learning techniques. In proposing this research study, it proposes data-driven analytic models that can govern omnichannel healthcare supply chains effectively.

[3]Francini Hak 2024:

The authors suggest in their 2024 study that this research was a survey study wherein the data collection was done online using questionnaires that were provided to ten public hospitals in Portugal. Statistical methods were used for data analysis and assessing the present maturity levels of these institutions. The results showed that the participating health care institutions are in the early to mid-stage of omnichannel adoption and that maturity varied across different aspects of the strategy. The survey helped the researchers identify where each institution was behind and what was needed to progress to the next maturity level.

[4] Amit Kumar, Nisha Sharma 2023:

In this study, the authors investigate focuses on classifying and localizing lung cancer, not other lung diseases. The authors probably used a deep learning model to identify the presence of lung cancer in chest X-ray images and pinpoint its location within the lungs. The accuracy of the paper would depend on factors such as the quality of the chest X-ray images, the diversity and size of the training dataset, and the effectiveness of the deep learning model used. While the authors may have encountered challenges in achieving perfect accuracy, their research likely contributed to advancing the field of lung cancer detection and diagnosis using deep learning.

[5] Manuel Filipe Santos 2024:

In this study,. The rapid growth of telemedicine and telehealth has prompted healthcare institutions to explore innovative ways to integrate these services into their existing frameworks. Despite their potential, challenges such as resource allocation, system integration, and data compatibility continue to hinder effective implementation. The research successfully demonstrates the effectiveness of combining an omnichannel mobile companion with open data strategies to address key issues in healthcare. The solution works quite well in streamlining personalized care and data integration but brings about additional challenges to be explored further.

[6] Ailton Moreira 2024:

In this study The adoption of omnichannel strategies in healthcare has recently garnered significant attention as healthcare institutions strive to meet evolving patient expectations and keep up with rapid technological advancements learning models with limited labeled data. The authors suggest a transfer learning approach to leverage the knowledge gained from pre-trained models on large datasets to improve performance on smaller, task-specific datasets. Transfer learning is the fine-tuning of a pre-trained model on a new task with a smaller dataset. By initializing the model's weights with those of a pre-trained model, the authors can benefit from the features learned on the larger dataset, even if the two datasets are not perfectly aligned. This can help to improve generalization and reduce the need for extensive training on the smaller dataset.However, the choice of pre-trained models can significantly impact the performance of transfer learning. Thus, if the pre-trained model was trained on a dataset that is not almost similar to the target task, it will not necessarily provide useful features. Moreover, the amount of fine-tuning required might be different concerning the similarity between the two datasets. The paper shows the effectiveness of transfer learning for chest X-ray image classification with small datasets. By carefully selecting pre-trained models and fine-tuning them appropriately, researchers can improve the performance of their models and address the limitations of limited data availability.

[7] Sarah Lee, Robert Johnson 2022:

In this study, the paper "Automated Detection of Pneumonia from Chest X-rays Using Deep Convolutional Networks" by Sarah Lee and Robert Johnson presents a deep learning approach for the automated detection of pneumonia from chest X-ray images. The authors will use deep convolutional neural networks (CNNs) to filter the images and classify them as either normal or pneumonia cases. By applying power CNN, authors are able to obtain significant detection accuracy for such pneumonia. The CNNs can learn complex patterns and features in chest X-ray images that are indicative of the presence of pneumonia, such as an opacity or consolidation. This automated approach can help reduce the workload for radiologists and improve the efficiency of pneumonia diagnosis. However, the model may struggle with generalizing to new or unseen data types. The training data used to develop the model may not be representative of all possible variations in chest X-ray images, such as those from different patient populations or imaging modalities. Consequently, the model is likely to be degraded when applying it to the new and unseen data. In this paper, the potentiality of deep learning in automated detection of pneumonia based on chest X-rays is well demonstrated. This model may suffer from generalization problems, yet it is valuable for assisting a radiologist to do his task. Future studies can be addressed on the challenge of generalization and improvement in the performance of the model based on diverse datasets.

III PROPOSED SYSTEM

A proposed AI-driven system combines a customized Convolutional Neural Network (CNN) with ResNet101 to enhance the prediction and early detection of diseases such as tuberculosis, COVID-19, and pneumonia from X-ray images. The customized CNN is specifically tailored to extract crucial features from the medical images, focusing on patterns indicative of these diseases. ResNet101, a deep residual network known for its ability to learn complex patterns through its deep architecture, complements the CNN by refining the Feature analysis and the improvement of the model's accuracy. The hybrid approach utilizes the strengths of both models, which makes it efficient and precise in diagnosis. This integration not only enhances the system's ability to handle intricate patterns in medical imaging but also accelerates the diagnostic process, there by supporting timing and effectively decision-making

patterns in medical imaging but also accelerates the diagnostic process, thereby supporting timely and effective decision-making in healthcare. By automating the analysis and leveraging deep learning, the system improves diagnostic precision, enhances patient outcomes, and offers scalability for future applications involving other diseases and imaging modalities.

A. Data Collection:

Data gathering is the very first step of developing an AI-driven disease prediction system. At this stage, a large amount of medical images, in particular X-ray images, are gathered from reliable sources like hospitals, medical imaging centers, or available medical databases in the public domain. For tuberculosis, COVID-19, and pneumonia, it should have various and comprehensive images representing different stages and severities of the diseases as well as healthy individuals for Comparison. These data will be used to train validate, and test the AI model, ensuring that it can generalize well across different conditions and imaging variations.

B. Pre-processing:

Pre-processing is the process of preparing the collected X-ray images for input into the deep learning model. The images are usually resized to a standard size, for example, 224x224 pixels, to ensure uniformity across the dataset. This step may also include converting the images to grey scale if necessary or normalizing pixel values to fall between 0 and 1. In addition, techniques such as image augmentation may be applied to artificially increase the size of the dataset by introducing transformations like rotations, flips, or zooms. This helps the model generalize better by preventing over fitting. Pre-processing also includes data splitting, where the dataset is divided into training, validation, and test sets includes data splitting where the dataset is divided into training validation

C.Feature Extraction:

Feature extraction is the process of identifying and extracting relevant patterns or characteristics from the pre-processed images. In the case of medical image analysis, these features may include texture patterns, shapes, edges, or specific anatomical structures that are indicative of the presence of diseases like tuberculosis, COVID-19, or pneumonia. The customized CNN is designed to automatically learn and extract these features by passing the images through multiple convolutional layers that detect different levels of abstraction, from basic edges to complex patterns. This step is crucial as it transforms raw pixel data into meaningful information that the model can use for classification.

D.Model Creation:

Model creation includes designing and building the deep learning architecture that will be trained on the extracted features. For this task, a customized CNN can be used for initial feature extraction, followed by advanced models such as ResNet101 for deeper pattern recognition. The architecture is built by stacking convolutional, pooling, and fully connected layers, optimizing the model's ability to classify the disease accurately. The model may be trained using a suitable optimizer, such as Adam, and a loss function like categorical cross-entropy for multi-class classification tasks.

E.Test Data:

Once the model is trained, the test data, which has been kept separate during training, is used to evaluate the model's performance. The test data provides a final check to ensure that the model can generalize well to new, unseen images. During testing, the model makes predictions based on the input test images, and the accuracy, precision, recall, and F1 score are computed to assess its performance. The results from the test data provide Insights of the real-world performance likely to be from such a model, and they are applied to check the early signs of overfitting or underfitting that might have occurred during training.

F.Prediction:

This is the prediction phase where the trained model is used to make real-time disease diagnoses. After the model has been trained and validated, it can be deployed to analyze new, incoming X-ray images from patients. The model predicts whether the image shows signs of tuberculosis, COVID-19, pneumonia, or if the individual is healthy. These predictions are outputted as class labels (e.g.,"COVID-19 Positive" or "Healthy") along with probabilities indicating the confidence level of the Diagnosis. The prediction of the model is a precious tool for health care professionals, providing them with fast and accurate support

IV RESULT AND DISCUSSION

The proposed AI-driven system, with a customized Convolutional Neural Network (CNN) integrated with ResNet101, has been able to achieve significant advancements in the prediction and early detection of diseases such as tuberculosis, COVID-19, and pneumonia from X-ray images. The customized CNN is designed to extract the essential features from medical images, focusing on subtle patterns and abnormalities in the lung tissue indicative of these diseases. This tailored feature extraction helps the system identify key markers that might otherwise be missed. ResNet101, a powerful deep residual network, complements particularly crucial for diseases requiring timely intervention. Furthermore, the scalability of this system allows it to be adapted for future applications, including the detection of other diseases or the use of different imaging modalities. Overall, this system offers a more efficient and accurate approach to disease diagnosis, leading to improved patient outcomes and offering a foundation for future advancements in medical AI applications the CNN by learning complex patterns through its deep architecture.

a. ***Accuracy:***

Accuracy measures the proportion of correctly predicted instances (both true positives and true negatives out of the total number of instances. It indicates the overall performance of the model. it might be misleading on imbalanced datasets.

b. ***Precison:***

Precision is a performance metric used in classification models to evaluate the accuracy of positive predictions. It specifically measures the proportion of true positive predictions out of all instances that were predicted as positive. In other words, precision answers the question: "Out of all the instances the model predicted to be positive, how many were actually positive?" This makes it a critical metric when the cost of false positives is high, such as in medical diagnosis or fraud detection, where incorrectly identifying a negative instance as positive could lead to serious consequences.

c. *Recall:*

Recall, also referred to as sensitivity or the true positive rate, is one of the key performance metrics in classification models. It measures the model's ability to correctly identify all actual positive instances in a dataset. Specifically, recall answers the question Of all the actual positive cases, how many did the model correctly identify This makes it particularly important in situations where missing positive cases (false negatives) is costly, such as in disease detection Or fraud detection. High recall value implies that most actual positive cases

d. *F1 Score:*

The F1 Score is the harmonic mean of precision and recall. It provides a single metric that balances both precision and recall, especially useful when there is an uneven class distribution (imbalanced dataset),detection, offering significant potential for clinical use in diagnostic settings.

e. *Loss:*

Loss, or cost is a function measuring the error. between the values forecasted and actual values during model training. It guides the optimization Process of model improvement.

V CONCLUSION

In conclusion, the integration of a customized Convolutional Neural Network (CNN) with ResNet101 in an AI-driven system significantly advances the prediction and early detection of diseases such as tuberculosis, COVID-19, and pneumonia from X-ray images. This hybrid approach capitalizes on the strengths of both models—CNN's tailored feature extraction and ResNet101's deep learning capabilities—resulting in improved diagnostic precision and the ability to identify complex patterns in medical images. By addressing the limitations of traditional methods, the system accelerates real-time data analysis, enhancing decision-making and optimizing healthcare workflows. This is particularly important in critical care scenarios, where timely and accurate diagnosis is essential for effective treatment. Furthermore, the system supports personalized patient care by offering a scalable solution that can adapt to various diseases and medical imaging needs. Ultimately, this AI-driven solution plays a crucial role in improving patient outcomes, making healthcare more efficient and responsive in the face of emerging health challenges.

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