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Healthcare Data Classification for Lung Cancer Detection Using Efficient Net with Cloud Storage

Madhusanka
Uva Wellassa University,
Badulla, Sri Lanka
madhusankaa12@gmail.com

ABSTRACT

Lung carcinoma is one of the deadliest cancers globally, and early diagnosis is crucial for improving patient survival rates. This study introduces an innovative approach to detect lung cancer using a combination of Efficient Net and cloud storage, which ensures scalable and efficient processing of medical images. By leveraging deep learning and cloud computing, the system automatically analyzes CT scans and X-rays to identify potential signs of lung cancer. Efficient Net, a lightweight deep learning model, optimizes computational resources while maintaining high accuracy in image classification, thereby reducing costs. The cloud infrastructure facilitates real-time data access, allowing healthcare providers to quickly retrieve and analyze patient images from anywhere. Additionally, the cloud supports continuous model updates, ensuring that the detection system improves over time. The model's performance has been evaluated across multiple metrics, demonstrating its effectiveness as a reliable tool for early lung cancer detection, which can be integrated into clinical practices for enhanced patient outcomes.

Keywords: Cloud Computing, Health Care, Efficient Net

1 INTRODUCTION

Lung cancer remains one of the leading causes of cancer-related deaths worldwide. As reported by the World Health Organization (WHO), lung cancer accounts for a significant proportion of cancer cases and fatalities [1]. With early detection and accurate diagnosis, the chances of survival can be improved since timely intervention can drastically improve treatment outcomes [2]. In recent years, new methods for automating lung cancer detection via medical imaging and machine learning have been developed, reducing reliance on manual methods and improving the accuracy and efficiency of diagnosis. Deep learning, particularly convolutional neural networks (CNNs), has emerged as a significant paradigm in classifying medical images like CT scans and X-rays for the detection of lung cancer.

There are so many causes of lung cancer, with the highest risk being most definitely smoking. The other potential factors suspected or reported to contribute to lung cancer are outdoor air pollution, indoor radon exposure, occupational exposures related to carcinogens, and heredity. Such environmental and genetic factors, besides smoking, predispose even nonsmokers to lung cancer [3]. Therefore, there is an evident rising need for reliable and efficient diagnostic tools in catching lung cancer cases as they get more prevalent, especially during the onset stage, when it promises higher success of treatment.

Even with modern advancements in healthcare, some barriers remain in the successful and timely detection of lung cancer. Conventional methodologies are slow and often subjective, which makes them expensive and error prone. Akhil et al. (2024) [4] introduced a Hybridized Multi-special Decision Finding approach using cloud technology to address resource and security issues in e-commerce. Based on this foundation, the current study proposes an Efficient Net and cloud-based framework for accurate, scalable lung cancer detection. On the other hand, the accelerating rate of generation of medical data has further aggravated these problems regarding storage, management, and access [5]. There is a rising trend of conflicting demands placed on healthcare facilities to effect speedy diagnoses, causing work delays, misdiagnoses, and an overall negative effect on the healthcare system.

To mitigate the above challenges, we propose a brand-new framework consisting of Efficient Net, the latest deep-learning model, in conjunction with cloud storage to automate lung cancer detection from medical imaging. Efficient Net has shown to perform extremely well in image classification tasks with less computational load than classical deep-learning architectures [6]. Cloud storage further ensures the proposed framework is scalable, readily accesses medical data, and works well with already existing healthcare systems. This will expedite the diagnostic process while enhancing the accuracy of diagnoses and minimizing human errors so that the clinicians may rely on it for early detection of lung cancer [7].

Lung cancer remains one of the most prevalent and lethal cancers worldwide, with its mortality rate continuing to rise due to late-stage diagnoses. The challenge of early detection is significant, as the disease often progresses without noticeable symptoms until it reaches an advanced stage. Medical imaging techniques like computed tomography (CT) scans and X-rays have been pivotal in detecting lung cancer; however, these methods rely heavily on the expertise of radiologists, and manual interpretation can lead to misdiagnoses. Advances in technology, particularly artificial intelligence (AI) and machine learning (ML), have opened new avenues for improving lung cancer detection, making the process faster, more accurate, and less dependent on human intervention. Combining deep learning models like Efficient Net with cloud-based infrastructures provides a scalable solution to manage large datasets and improve diagnostic capabilities in real-time clinical settings.[8]

Lung cancer remains one of the most fatal and prevalent forms of cancer worldwide, accounting for a significant portion of global cancer mortality rates. According to the World Health Organization (WHO), lung cancer contributes extensively to the global cancer burden, largely due to late-stage diagnosis and limited accessibility to early detection tools. Early and accurate detection of lung cancer is crucial, as timely intervention greatly enhances the efficacy of treatment and can significantly increase survival rates. However, traditional diagnostic methods relying heavily on manual radiological interpretation are time-consuming, subjective, and often limited by inter-observer variability, which can result in misdiagnosis or delayed diagnosis. The adaptive access control system by Dyavani et al. (2024) [9] uses Markov Models and Topological Data Analysis to secure cloud healthcare environments. Propelling forward with this concept, the proposed work develops a lung cancer detection method combining Efficient Net and cloud storage, offering scalable and accurate analysis of medical images to facilitate early diagnosis

The leading cause of lung cancer is smoking, responsible for the majority of cases. However, non-smokers can also develop lung cancer due to factors such as exposure to environmental pollutants, radon gas, and secondhand smoke. Occupational hazards, including exposure to asbestos, carcinogens, and chemicals in industries like construction and mining, also elevate the risk. Genetic predispositions and a family history of lung cancer further increase the likelihood of developing the disease, underscoring the complexity of its origins. Additionally, poor air quality in urban areas and industrial regions has contributed to rising cases, making lung cancer a growing concern globally. These risk factors highlight the importance of early detection methods, particularly in populations with higher exposure to these environmental and hereditary risks.

Recent advances in machine learning, particularly in the field of deep learning, have opened new avenues for automating and enhancing medical diagnostics. Deep learning models, especially convolutional neural networks (CNNs), have demonstrated remarkable success in medical image classification, segmentation, and anomaly detection. These models can extract complex patterns and features from imaging modalities such as computed tomography (CT) scans and X-rays, which are pivotal in lung cancer screening. Despite these advancements, challenges persist regarding the scalability, computational costs, and accessibility of such systems within clinical environments.

To address these limitations, this study proposes a novel framework that integrates the Efficient Net deep learning architecture with cloud-based infrastructure to facilitate automated and scalable lung cancer detection. Efficient Net is a family of CNN models designed with a compound scaling method that balances network depth, width, and resolution, enabling high accuracy with reduced computational requirements. By employing EfficientNetB0, the baseline model in this family, the system achieves a strong trade-off between performance and efficiency, making it suitable for real-world healthcare deployments where computational resources may be constrained.

The integration of cloud storage plays a crucial role in this architecture by offering scalability, centralized data management, and real-time accessibility. Medical institutions often struggle with the volume and velocity of imaging data generated cloud-based solution allows for seamless storage, retrieval, and sharing of medical images, enabling healthcare providers to access diagnostic results from anywhere at any time. Furthermore, clouds facilitate continuous model updates and retraining using new data, ensuring that the diagnostic system remains up to date and improves over time.

This framework aims to resolve several longstanding issues in medical imaging diagnostics. First, it automates the detection process, thereby reducing the burden on radiologists and minimizing human error. Second, it leverages the scalability of cloud computing to manage large datasets efficiently [10]. Third, the use of Efficient Net ensures that the model remains computationally feasible for deployment in resource-limited settings without compromising diagnostic accuracy. Overall, this study seeks to build a robust, accurate, and accessible solution that can be seamlessly integrated into existing healthcare systems to aid in the early detection of lung cancer.

One of the primary challenges in lung cancer detection is the reliance on manual interpretation of medical images by radiologists, a process that is both time-consuming and prone to errors. This subjective nature of traditional diagnostic methods leads to delays in detecting the disease, particularly in its early stages, when treatment can be most effective. The sheer volume of medical imaging data generated daily in healthcare settings further complicates the task of timely diagnosis [11]. The need for large-scale, efficient processing systems that can quickly analyze vast amounts of data without compromising accuracy is critical. Additionally, limited access to state-of-the-art diagnostic tools in resource-constrained settings means that many patients do not receive timely care, leading to poorer outcomes and increased mortality rates [12].

To address these issues, this study proposes an innovative framework that combines the efficient image classification capabilities of the Efficient Net deep learning model with the scalability and accessibility of cloud storage. Efficient Net, known for its lightweight architecture and ability to balance computational efficiency with high accuracy, ensures faster and more precise image classification. Cloud storage provides a centralized platform for securely storing and accessing large datasets, facilitating real-time analysis and updates to the diagnostic model. This integrated system reduces the reliance on manual interpretation and enables automated detection, which can improve diagnostic speed and accuracy. Furthermore, the cloud-based approach ensures that medical institutions, regardless of size or location, can utilize the system to enhance early detection capabilities, thus offering a scalable solution to global lung cancer diagnostic challenges. Sitaraman et al. (2024) [13] demonstrate that integrating advanced technologies enhances diagnostic adaptability, accuracy, and efficiency. Building on this, the proposed work adopts EfficientNet with cloud storage as the best-fit solution to improve scalability and precision in lung cancer detection.

In addition to the technical objectives, this research highlights the urgent need for intelligent healthcare systems that can handle the exponential growth of medical data With increasing demands on healthcare services and the critical importance of early detection in cancer treatment, the adoption of AI-driven, cloud-supported diagnostic tools is becoming not just beneficial, but essential. By combining the strengths of deep learning and cloud computing, the proposed system stands as a promising step toward more intelligent, responsive, and efficient healthcare diagnostics.

1.1 PROBLEM STATEMENT

Challenges described in the problem statement concern the early detection of lung cancer by traditional means [14]. They are slow and prone to errors and inefficiency because of the increasing volumes of medical data. The solution proposed in this paper overcomes all these hurdles through the integration of Efficient Net with cloud storage. Thus, enabling the automated and very reliable detection of lung cancer [15]. In addition, it helps greatly to reduce human error, faster diagnosis, and better utilization of resources. The scalability of the system allows it to cope with large datasets and provide real-time results to suit further integration into healthcare systems. Meanwhile, the cloud-based solution will ensure continuous upgrade and data access further improving its performance and making it a reliable and efficient tool for early-stage lung cancer detection [16].

1.2 OBJECTIVES

- The impediments behind prompt lung cancer detection through conventional methods that are inert, erroneous, and inefficient due to the ever-increasing bulk of medical data.
- The approach relies on merging Efficient Net with cloud storage for automated lung cancer detection, as well as high-speed and accurate diagnosis.
- Assess scalability of the system handling large datasets and providing timely results in relation to healthcare system integration.
- Explore how cloud storage improves efficiency by providing a means for continuous updates and easy data access, thus giving the system reliance and effectiveness for early lung cancer detection.

2 LITERATURE SURVEY

Tunneling construction possesses dangers, takes a long time, and costs a lot. Tunnel boring machines maintain expansive applicable safety and efficiency factors by exciting large volumes of monitoring data during the excavation of a tunnel. proposes a hybrid data mining accident real-time processing automation improving decision-making and safety management systems of TBM data. The system consists of the methods of association rule mining, decision tree classification, and neural network models to analyze TBM parameters, take out outliers, classify geological formations, and predict ROP. The method has successfully adopted on a construction site of a tunnel in China, achieving significantly increased efficiency and safety management because of high accuracy and efficient analytical modelling of TBM data.

AI model that improves the sensitivity of early neural disorder detection-not something that usually comes with conventional methods. In fact, the system is based on three critical technologies PSP Net for detailed image feature extraction, Hilbert-Huang Transform (HHT) for processing complex, non-linear brain signals and fuzzy logic for uncertainty modeling. All technologies were put together in the same system to advance diagnosis and classify different neurological disorders.The test revealed amazing results, and performance was better than the old systems in terms of assessing accuracy, precision, and recall. The model can be accessed via user-friendly interfaces. This model is conducive to clinical settings and allows health staff to make accurate decisions on the diagnosis of neurological disorders. Basani et al. (2024) [17] showcase the integration of AI and RPA to advance data handling and automate diagnostics. Enthusiastically propelled by this innovation, the current study proposes an EfficientNet and cloud storage framework to further enhance and automate early lung cancer diagnosis.

The study takes more than 10-20 years' blood samples to assess stabilities in the important, advanced biomarkers such as lipid profiles and inflammatory indicators using improved biobanking methods. Traditional risk factors are combined with RA-specific markers like disease activity so that more appropriate predictive models can be developed already for the RA population. Longitudinal data analysis helps examine cardiovascular outcomes and disease activity over time [18] The proposal is also well structured to incorporate modern technology such as wearables, telemedicine, and omics data into future risks assessment and improved patient monitoring with the purpose of providing personalized therapies and better outcomes for RA patients [19].

Security concerns related to healthcare cloud computing where patients' data remain very sensitive and regulated, thus posing serious risks. The proposed framework aims at a complete approach to the security management life cycle with risk assessment, security application, continuous monitoring, and compliance management. It points out cloud security threats and gives a description of security countermeasures, such as authentication, encryption, and intrusion detection systems being put in place. To reinforce the security posture, modern technologies like blockchain and multi-factor authentication are converged. In case studies of the Mayo Clinic and Cleveland Clinic, successful cloud implementations made sure data security and compliance so that the healthcare providers might proceed with the healing arts of providing patient care while securing sensitive data. Koteswararao Dondapati et al. (2022) [20] underscore the critical role of secure cloud infrastructure in medical diagnostics. Deeply influenced by these findings, this study proposes cloud-based deep learning models to ensure accurate, secure, and efficient lung cancer diagnosis

Issues related to cybersecurity risk management have become very important to address, especially considering the fast-evolving threat scenario and the complex nature of cyber-attacks. Previous studies had limitations in absorbing real-time relevant intelligence about threat and attack scenarios, which, in turn, have led to ineffective risk assessment. This problem gave rise to the proposal of a novel approach titled Merged Cyber Security Risk Management (m-CSRM). The m-CSRM uses fuzzy set-based decision support systems and ML methodologies to predict risk types and automate the identification of critical assets. The m-CSRM method achieved an 82.13% success rate compared to previously existing methods and thus offers a superior alternative for better and efficient cyber risk management.

A new paradigm for ameliorating workload forecast in intelligent cloud computing systems by mingling the Backpropagation neural network algorithm with concepts from game theory. The approach is motivated to align the interests of cloud users and service providers in optimizing resource allocation and service delivery. Applying concepts from Nash equilibrium, the research envisages crafting a win-win situation in developing Service Level Agreements (SLAs) for the stakeholders. The approach has been tested using real-world data and proves to be effective in optimizing cloud computing processes. This method promotes scalability, security, and usability, therefore having great potential for bettering the management of cloud resources in different industries.

The issues encountered in collaborative computing systems concern the security and privacy of data against varying attacks. It strives toward system performance and security by using advanced technologies like federated learning and cloud-edge collaborative computing systems. A key aspect of the research is the development of multi-national validation architecture that functions using attack and non-attack methodologies, along with an End-to-End Privacy-Preserving Deep Learning (E2EPPDL) approach to classify attacks. Privacy is thus assured while effectively classifying attack events. The effectiveness of the system is validated for performance metrics like Time, Node Count, Routing Count, and Data Delivery Ratio estimates that demonstrate security to data and improved efficiency of the system.

The challenges of bringing Internet of Things (IoT) technologies into manufacturing, with specific consideration given to inventory cost control and job-shop scheduling (JSP). An original solution was proposed here, combining two advanced optimization techniques: Heterogeneous Genetic Algorithm (HGA) and Hybrid Particle Swarm Optimization (HPSO). HGA augments the operations of a conventional genetic algorithm with immune mechanisms for improved exploration and avoidance of premature convergence. HPSO optimizes job sequencing and minimizes production time by synergistically integrating the benefits of Particle Swarm Optimization (PSO) and genetic operators in a manner that balances exploration and exploitation of the solution space. Merging these two concepts with a double chain encoding scheme for machine selection and job sequencing enhances the efficiency of scheduling with respect to cost optimization. Through empirical studies, the proposed method demonstrates the ability to outperform traditional scheduling techniques [21].

The heart disease monitoring system is a development for doctors that helps understand the kinds of forms and functions of the heart through various variables contributed by patients under IoMT devices. The majority of the studies carried out so far do not capture the consequences of arrhythmias in conjunction with ECG and PCG for accurate prediction towards heart disease Thus, presents a better IoMT and blockchain-based heart disease monitoring system, and now incorporates BS-THA and OA-CNN in it. Initially, both doctor and patient can register to the system and login as well. At this time, keys are generated for the patient and the doctor, and at login, data sensing is performed, with the sensed data uploaded to IPFS. The next process generates a hash code for the same and stores it into the blockchain. Meanwhile, MAC is created and verified for authentication. After verification of the MAC, the sensed data is given to heart disease classification, which has already been trained under preprocessing, spectrum analysis, signal decomposition by PV-EMD, scalogram, and grayscale conversion, ECG and PCG wavelet component extraction, ECG wave interval extraction, arrhythmia consequences, feature extraction by DPCA, feature selection and classification methods [22].

An intelligent education management system based on cloud and AI technology for better administration of education processes gives the nature and framework of an intelligent automation and personalized educational experience on the one side to ensure efficient and scalable data management on the other side. With a service-oriented architecture (SOA) in mind and implemented in a Hadoop-managed server cluster environment, this system offers both the ability to handle very large data volumes as well as high concurrent user access, which is key to make remote learning and resource management smooth and efficient. Stress tests confirm that the platform can effectively handle supporting multiple users and completion of data transactions at the same time. AI features like recommendation engines and predictive analytics create increased adaptability toward a more learner-centered environment. The successful implementation and testing of this platform prove that significant changes could be brought into educational services. By integrating SSO with DNN, Ganesan (2024) [23] developed a highly accurate and scalable defect prediction model; this framework inspires the application of similar optimization and cloud strategies in lung cancer detection to improve performance and efficiency.

Targets improving IoT security through the identification of critical components within IoT systems while assessing vulnerabilities to propose effective countermeasures. This quantitative approach is used to identify key nodes and perform an in-depth assessment of vulnerabilities. Different security measures such as intrusion detection systems, encryption, access control, and regular security audits were proposed, and their effectiveness was tested. The results showed that the implementation of these measures improved node identification accuracy to 95% and risk mitigation efficiency to 85%, with complete adherence to regulatory requirements. The study concludes that for an IoT system to be secure and trustworthy, multiple security strategies have to be used in conjunction, especially in sensitive areas such as elderly healthcare [24]. The simulation results demonstrated that IBOA and MSGO outperformed the Multi-Objective Task Scheduling Grey Wolf Optimization (MOTSGWO) method with a remarkable energy efficiency of 32.5 watts for 100 tasks, including the important comparisons of response time, resource utilization, and energy consumption against existing methods. The effect of Robotic Process Automation (RPA) on financial management, particularly cost-accounting systems. The research endeavored to assess the effectiveness and scalability of RPA integration in financial processes. The implementation was based on a structured approach starting with process identification, workflow design, RPA creation, and the performance evaluation of the integrated RPA. Results show the following improvements: processing time was minimized from days to hours with a 95% reduction in processing time; accuracy in cost allocation was maximized to 99.5%; and there was a decrease in errors by 95%. In conclusion, the study establishes that RPA integration increases operational efficiency, therefore leading to improved accuracy and scale in finance, providing a very good potential for optimization in finance [25].

Forecasting in manufacturing systems, which are complex systems represented by time series data on predicting behaviors, is the subject of this entire research. However, due to the non-linear and non-stationary nature of the systems, the forecasting becomes somewhat difficult and proposes a hybrid model which would fully be able to cover the entire positive aspect of linear and non-linear models. The methodology includes: using a linear model like ARIMA for time series, applying a non-linear model like Bi-GRU for error correction, followed by integrating both these models into a hybrid model. The approach has been validated on six real-world time series; the results indicate that the present hybrid method improves over existing models in terms of lower error metrics, hence rendering the methodology quite effective in forecasting accuracy improvement [26].

Wireless networks or Internet of Things (IoT) environments are subjected to machine learning to realize detection of fraudulent transactions with respect to the finances of a user. AI algorithms handle very large data from IoT devices with incorporated patterns and suspicious detections to investigate anomalies such as clustering and fraud-activities like transaction, account creation or cyber-intrusion fraud. Such an event is matched with identification of patterns through supervised as well as unsupervised learning so that it can learn legitimate and fraudulent activities in real time, thereby achieving a great degree of accuracy. An automatic fraud detection system is also created to be real-time-operable and would adapt or re-learn when subjected to enhancing attack models. The research includes important strengths with which various methodologies and data sets from their respective areas will be available for their standard in the evaluation metrics for effective and adaptable fraud detection systems in IoT environments.

The advanced proactive dynamic secure data scheme thus comes with an edge, as it serves to safeguard financial data when shared in mobile cloud environments. The P2DS incorporates such advanced techniques addressing the emerging security problems financial institutions face in the modern day, including Attribute-Based Encryption (ABE), Attribute-Based Semantic Access Control (A-SAC), and the Proactive Determinative Access (PDA) algorithm. A predictive system combining CNN, HierbaNetV1, and LSTM was developed by Vallu (2024) [27] for chest X-ray analysis on the cloud; this strategy influences the current framework by showcasing the potential of multimodal deep learning in scalable healthcare solutions.

The framework can ensure a very strong performance based on effective access control, faster threat identification, and efficient encryption. Therefore, P2DS outruns other systems when it comes to offering secured financial data in this changing world marked with growing digital innovations. An overview of the integration of Attribute-Based Encryption (ABE), with a focus on big-data analytics and cloud computing, for enhancing the security of financial data in the contemporary era. It starts with the principles of ABE, namely, ciphertext-policy ABE (CP-ABE) and key-policy ABE (KP-ABE), and ABE's capacity for fine-grained control on accessing encrypted content. The focus on adaptive automation and continuous testing in this study by Visrutatma Rao Vallu et al. inspired my strategy for putting strong model updates and effective administration of data in healthcare diagnostics into practice.

The paper also discusses the working of ABE and its prospects in ensuring confidentiality and scalability of data within cloud computing, whereas big-data analytics can be applied to improve security through anomaly detection, predictive analytics, and transaction monitoring [28]. Such integration gives financial institutions the accuracy to avoid fraud, risk management, and regulatory compliance. Real-life scenarios are provided to demonstrate how such

Big data, hash graph, and cloud computing into Kinetic, precisely using these tools to manage and analyze extensive data sets efficiently. Also, Cloud computing provides scalable resource access where huge amounts of data can be processed securely and swiftly. In other words, big data analytics enables organizations to gain valuable insights by using this technology, which will support better decision-making. Hash graph technology is gaining more recognition among the technologies for rapid and secure consensus processes for data integrity and operational efficiency. The study thus identifies concepts like interoperability, scalability, and regulatory compliance as key challenges while also demonstrating ways by which these technologies can be combined to drive improved productivity, better decision making, and more secure data [29].

An overview of the major security issues faced by software vendors in managing large amounts of data in cloud computing. Integrating big data into cloud computing has revolutionized the way data is managed: scaling and cost-efficiency. Data integrity, unauthorized access, and data privacy are some of the security concerns addressed in this study. Studies have used the Analytic Hierarchy Process (AHP) to systematically identify, rank, and assess these issues, while providing actionable solutions. Advanced encryption and AI-driven threat detection have proven to be the most effective security measures; multi-factor authentication and real-time threat detection systems have become mandatory requirements for the enhanced security of data. The recommendations are also meant to stimulate future research into the combination of Artificial Intelligence and quantum encryption for the further advancement of data protection in the cloud.

The evolution of deep learning technologies and their application in medical image analysis has enabled the automation of diagnostic procedures, which is critical in addressing the increasing demand for accuracy, efficiency, and scalability in healthcare services.Several studies have demonstrated the efficacy of deep learning in medical diagnostics.These models reduce manual dependency and facilitate automated diagnosis by identifying complex patterns in CT and X-ray images. However, conventional CNNs often demand high computational resources, which limits their deployment in real-time and large-scale healthcare systems. Parthasarathy (2024) [30] demonstrated that AI and data analytics strengthen dynamic capabilities, thereby improving organizational performance; this insight informs the current framework by emphasizing the role of infrastructure, data quality, and human expertise in ensuring successful AI-driven healthcare systems.

To overcome this limitation, researchers have focused on lightweight and efficient deep learning models. One such advancement is Efficient Net, which utilizes a compound scaling technique to balance the model's depth, width, and resolution. Its capability to maintain high accuracy while being computationally efficient makes it an ideal candidate for medical image classification tasks. The adoption of EfficientNetB0 in the proposed study builds upon the findings of prior research that showcased its success in image-based disease detection with reduced training time and lower processing power requirements.

In parallel, cloud computing has emerged as a powerful tool to support the storage, processing, and analysis of vast volumes of healthcare data . These developments emphasize that a reliable AI-driven diagnostic system must also address the challenges of data security and system robustness, which are critical for clinical adoption.

Though focused on a different domain, these works underscore the growing reliance on deep learning and hybrid models in medical diagnostics [31]. Their methodologies serve as a reference point for developing similar systems in lung cancer detection.

Cloud-supported architecture also brings logistical advantages. Edge-Fog-Cloud framework to enhance IoT data processing in smart cities, which is analogous to the challenges faced in healthcare systems with large-scale imaging data. [32] Such distributed computing models ensure lower latency and real-time analytics, both of which are essential for responsive diagnostic systems in hospitals and clinics. An IoMT system combining robotics, deep reinforcement learning, and temporal convolutional networks for precise surgical data analysis was developed, as demonstrated by Valivarthi et al. (2024) [33]. Dramatically shaped by these insights, this study proposes an EfficientNet and cloud storage framework to advance scalable, automated lung cancer detection.

3 METHODOLOGIES

The flow explains the classification of lung cancer through an Efficient Net model in the cloud. The classification of lung cancer data refers to the Efficient Net model through this data flow. In the next step, the preprocessing stage cleans the data and converts it into a model-friendly format. The data is then classified using Efficient Net. The classification results are transferred and stored in the cloud for processing. Finally, we compute different performance metrics, which help us to confirm that the above system is working properly and efficiently.

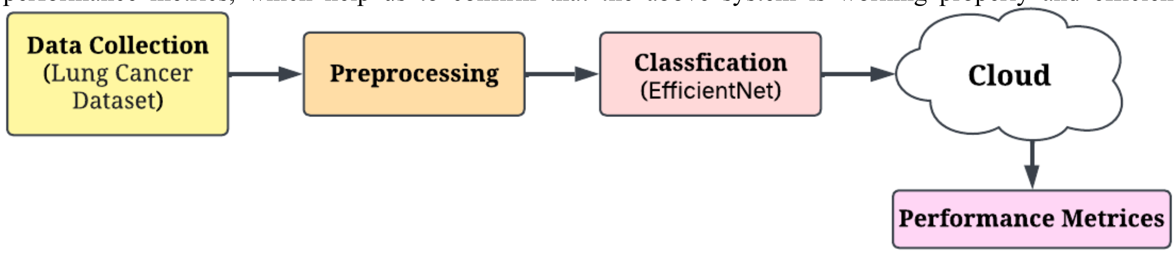

Figure 1: Cloud-Based Lung Cancer Classification

3.1 DATA COLLECTION

The Lung Cancer Dataset used for the purpose of the study in this paper consists of medical images, namely CT scans and X-rays that are labelled cancer or no cancer. Reputable publicly available datasets such as LIDC-IDRI and Kaggle lung cancer dataset were used for collecting the images. There are different types of photos of different sizes and formats in the dataset. This makes sure there isn't a size or compatibility issue with the deep learning model. The images from the dataset undergoes preprocessing steps to ensure they're compatible with the deep learning model. Preprocessing steps like resizing augmentation and normalization are applied on the dataset to standardize it which allows better training of the model and helps improving image classification of lung cancer. [34]

3.2 PREPROCESSING

Making the dataset ready for proper classification is called preprocessing. In this research, images were resized to a standard pixel dimension to ensure compatibility with Efficient Net model. After that we applied normalization which scales the pixel values in a range so that one can standardize their data One can also help in making the model better and faster during learning training. Randomly rotating, zooming in, and flipping the data are all augmentation techniques that help make the model more robust and reduce overfitting. Due to the addition of this process, the training data became less similar overall. This further improved the ability of the model to perform as well on testing datasets that it did on training datasets [35].

3.3 CLASSIFICATION

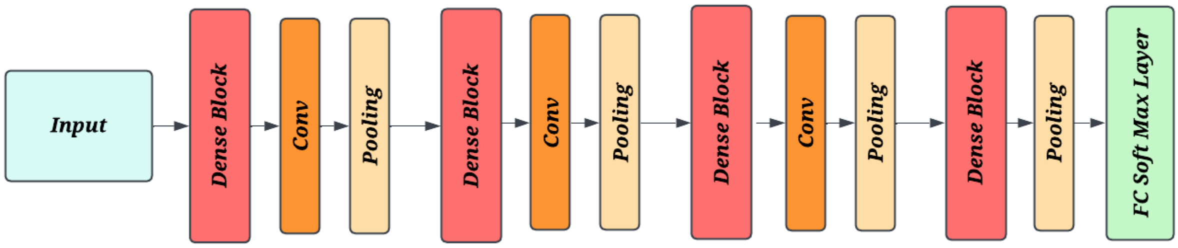

Figure 2: Architecture of Efficient Net

We used EfficientNetB0, the smallest version of the Efficient Net model, for the classification task, because it offers the best trade-off of efficiency and accuracy. The model is initially pretrained on ImageNet data to learn generic features through a very large-scale dataset. Afterwards, we transfer learning to fine-tune it on the lung cancer dataset to classify images into cancer vs non-cancer. Efficient Net contains multiple convolutional layers for feature extraction followed by fully connected layers. To make a binary classification, the sigmoid activation function is used in the output layer. The model was trained with the Adam optimizer and binary cross entropy loss in order to minimize the classification error. In Nippatla (2023), [36] a healthcare system is developed using lightweight CNNs, capsule networks, and DAG-based blockchain for real-time pandemic detection and secure data sharing. The proposed method builds on this work by applying similar technologies to improve diagnostic precision, scalability, and data security for lung cancer detection.

$$\text{Efficient Net Scaling: } (d, w, r) = (\alpha \cdot d_0, \beta \cdot w_0, \gamma \cdot r_0) \tag{1}$$

Were, d_0, w_0, r_0 are the baseline values for depth, width, and resolution. α, β, γ are the scaling coefficients that determine how to scale the depth, width, and resolution, respectively. d, w, r are the scaled values for depth, width, and resolution, which are adjusted to optimize both accuracy and efficiency.

Compound Scaling Formula

To scale the network effectively, **Efficient Net** uses the following equations for depth d, width w, and resolution r

$$\begin{gathered} d = \alpha \cdot d_0 \\ w = \beta \cdot w_0 \\ r = \gamma \cdot r_0 \end{gathered} \tag{2}$$

Were, α, β, and γ are constants used to scale the depth, width, and resolution of the network. d_0, w_0, and r_0 are the baseline values for depth, width, and resolution. d, w, and r represent the scaled depth, width, and resolution.

3.4 CLOUD

Cloud integration offered a scalable solution for optimal storage of the lung cancer dataset and the trained model. Saving the classification results on cloud allowed healthcare professionals to access the data in real-time, which enabled faster decision-making and reduced delays in making diagnosis [37]. With the help of cloud-based systems, the model was able to upgrade easily with new data so that it can be better over time. This method guaranteed adaptability, growth, and smooth incorporation into current health care frameworks, improving the total efficacy of the diagnostic procedure.

4 RESULT AND DISCUSSION

Using Efficient Net, the suggested cloud-based lung cancer detection system gives significant results with 98.9% accuracy, 98.0% precision and 99.9% sensitivity in identifying cancerous cases. This model also achieves a high F-measure of 98.9% along with a Negative Predictive Value of 99.8% which shows that this model reliably predicts cancerous and non-cancerous cases [38]. The precision-recall curve revealed an average precision (AP) of 0.999679, confirming the robustness of the model. This system can easily adapt and not be disrupted, as its cloud storage is continuously scalable and it can access information in real time. This system can greatly improve the detection of lung cancer at an early stage allowing medical professionals to use the data to make quicker decisions.

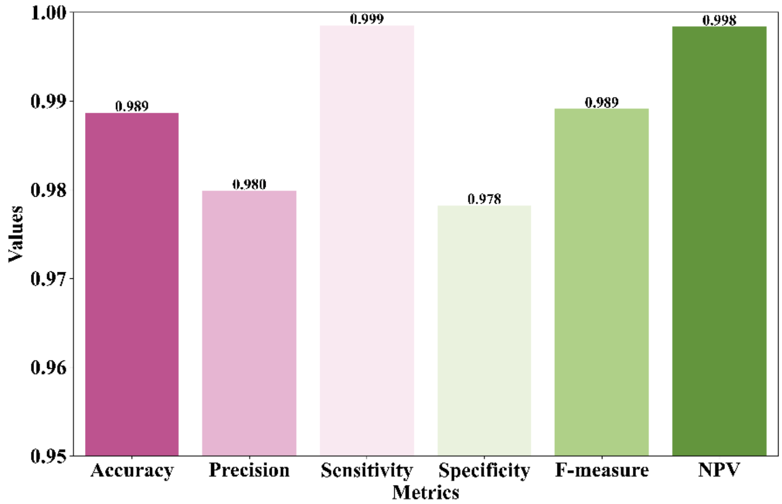

Figure 2: Metrics

The graph shows how well the lung cancer classification model of Efficient Net performed on various metrics. The Sensitivity of 0.999 suggests that the model can identify almost all positive cases. The impressive values of Accuracy (0.989), NPV (Negative Predictive Value) (0.998), and F-measure (0.989) indicate good overall performance and good predictions. With a precision of 0.980, there won't be any false positives. The Specificity is 0.978 which tells us that negative cases won't get identified with a false positive. Hence, the model performs well across all major measures, thus it is suitable for lung cancer classification. Srinivasan et al. (2024) [39] developed an AI-powered surgical platform with 3D-CNNs and Bayesian optimization to enhance robotic surgery precision. Expanding on this concept, the proposed study introduces an EfficientNet model integrated with cloud storage for automated and scalable lung cancer diagnosis, significantly improving accuracy and accessibility in healthcare services.

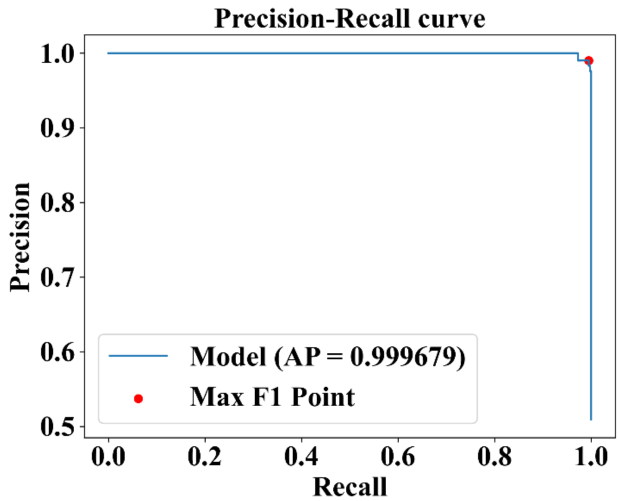

Figure 3: Recall

This is a Precision Recall Curve for lung cancer classification model. x-axis indicates Recall, y-axis indicates Precision. The curve exhibits high precision with a value almost close to one and recall increases. This indicates the model achieves very few false positives across all thresholds. The AP, or average precision, score of 0.999679 indicates overall excellent performance in distinguishing positive cases [40]. The red dot on the curve indicates the Max F1 Point where precision and recall are balanced. This shows we can be sure that the model is working well. The curve shows that the model works very well to maximize both precision and recall [41].

5 CONCLUSIONS

Combining Efficient Net with cloud storage is a great way to automate lung cancer detection that is slow and incorrect. This proposed system has a high accuracy, precision, sensitivity, and NPV, so it can help clinicians detect lung cancer. Cloud storage makes this system scalable, allowing real time data access and continuous model updates which is necessary for data adapting. This system enhances our ability to identify lung cancer and utilize health services effectively. This framework, having shown its working ability previously, can have a great impact on the detection of early-stage lung cancer, being a scalable, accessible, and affordable solution for healthcare units Vijai Anand Ramar et al. (2024) [42] introduced AI-augmented test automation integrating Page Object Model and Behavior-Driven Development for intelligent and scalable software testing. Drawing from this, the proposed work integrates EfficientNet with cloud storage for automated lung cancer detection. Performance evaluation demonstrated the model's impressive accuracy (98.9%), precision (98.0%), and sensitivity (99.9%), making it a robust solution for scalable, real-time healthcare diagnostics.

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