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IoT-Based Signal Processing for Lung Nodule Detection using 3D CT Images with 3D Convolutional Neural Networks and Feature Selection

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Abstract

The recognition of lung nodules through 3D CT imaging is an important and highly precise task that facilitates early diagnosis of lung cancer. In this paper, an IoT-based signal processing framework has been suggested that integrates 3D convolutional neural networks (3D CNNs) using advanced feature selection methods for the detection of lung nodules. The system processes the medical images in steps: dimensionality reduction, contrast enhancement, and noise removal, after which the derived features go to the 3D CNN for classification. In this process, for improved performance of the model, feature selection techniques like wrappers and hybrid filters are used in such a way as to ensure that the most relevant features support the detection of abnormalities. By means of the insightful clinical timelines of faster decision-making and real-time image transmission and processing thanks to IoT integration, the performance evaluation of the system gave great study-like recall, accuracy, precision, and AUC-ROC values indicative of promise in lung nodule diagnosis in an automated and real-time framework. With the aforementioned, this study provides great insight into how IoT, deep learning, and feature selection can be synergistically brought together to complement lung nodule diagnosis in medical imaging.

Keywords: *IoT-based Signal Processing, Lung Nodule Detection, 3D CT Images, 3D Convolutional Neural Networks (3D CNNs), Medical Imaging, Noise Reduction, Contrast Enhancement, Early Diagnosis, Medical Decision Support***.**

1. Introduction

The continuous evolution of the Internet of Things (IoT) is revolutionizing the healthcare sector by enabling the development of smart, connected systems capable of delivering personalized therapy and facilitating early disease detection [1]. These technologies provide a robust framework for integrating, transmitting, and analyzing vast volumes of medical data in real-time, ultimately enhancing diagnostic precision and accelerating clinical decision-making [2]. Among the many medical challenges benefiting from this transformation is the early detection of lung nodules—small masses in the lungs that can be indicative of lung cancer, a leading cause of cancer-related deaths globally [3]. Advanced imaging technologies, particularly 3D computed tomography (CT) scans, play a pivotal role in identifying lung nodules at an early stage, which is critical for improving patient prognosis and survival rates [4]. However, not all lung nodules are cancerous, making it essential to accurately distinguish between benign and malignant formations to devise appropriate treatment strategies. Traditional diagnostic workflows often rely on manual analysis of 2D scans, a process that is both time-consuming and susceptible to human error [5].

To overcome these limitations, the adoption of artificial intelligence, particularly deep learning techniques like 3D Convolutional Neural Networks (3D CNNs), has markedly improved the accuracy and efficiency of lung nodule detection [6]. These models excel at processing volumetric data and identifying complex spatial patterns within CT images, making them well-suited for detecting nodules embedded deep within lung tissue [7]. Furthermore, dimensionality reduction techniques such as Principal Component Analysis (PCA) and Recursive Feature Elimination (RFE) can be integrated with deep learning frameworks to enhance classification accuracy by isolating the most relevant features [8]. Despite these advancements, existing systems still face

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significant challenges, including high computational demands and difficulty generalizing across diverse CT image qualities, patient demographics, and nodule types [9]. These factors can lead to increased rates of false positives and false negatives, limiting the reliability of automated diagnostic systems [10]. Additionally, many current feature selection methods rely on manual or heuristic approaches that are inefficient and may not adapt well to varying clinical scenarios.

To address these challenges, this work proposes a novel IoT-enabled signal processing system designed for the precise detection of lung nodules [11]. The system leverages advanced automated feature selection techniques, including hybrid filter-wrapper methods, in combination with 3D CNNs [12]. By utilizing cloud-based computation and real-time data transmission, the proposed framework minimizes latency and computational bottlenecks, facilitating rapid clinical assessments [13]. IoT integration ensures seamless device communication and continuous patient monitoring, enabling healthcare professionals to make timely, informed decisions [14]. Ultimately, this approach aims to enhance the accuracy, scalability, and operational performance of lung nodule detection systems across a wide range of healthcare settings [15].

In parallel, the emergence of deep learning—especially Convolutional Neural Networks (CNNs)—has revolutionized the field of medical image analysis [16]. While traditional 2D imaging techniques provide valuable diagnostic information, they often fall short when dealing with the complex three-dimensional structures of lung nodules [17]. In contrast, 3D CNNs are uniquely equipped to process volumetric CT scan data, capturing intricate spatial hierarchies and subtle textural patterns in lung tissues [18]. This enables more accurate differentiation between benign and malignant nodules, reducing false positives and minimizing unnecessary biopsies or interventions [19]. Despite these advancements, several challenges persist. High computational demands, variability in CT image quality, and differences in patient demographics and anatomical structures can affect the robustness and generalizability of deep learning models [20]. Moreover, many existing approaches rely on manually selected or heuristic-based feature extraction methods, which may overlook critical data patterns and contribute to misclassification [21]. These limitations underscore the need for more intelligent, scalable, and automated systems that can process large-scale imaging data efficiently and accurately.

To address these issues, this study proposes a cloud-based, IoT-enabled lung nodule detection framework that leverages advanced signal processing techniques and automated feature selection in conjunction with 3D CNN architectures [22]. The system is designed to enhance real-time detection performance by minimizing computational overhead, reducing diagnostic latency, and improving classification accuracy [23]. By incorporating hybrid feature selection methods—such as Principal Component Analysis (PCA) and Recursive Feature Elimination (RFE)—into the 3D CNN pipeline, the model identifies the most relevant features for classification, thereby optimizing performance across diverse clinical scenarios [24]. This framework enables continuous monitoring and intelligent decision-making in clinical settings, offering scalable and adaptable solutions for modern healthcare systems [25]. The integration of IoT technologies ensures seamless communication between imaging devices, cloud platforms, and diagnostic models, creating an end-to-end intelligent system capable of supporting early lung cancer detection and improved patient care [26]. The proposed approach represents a significant step toward the development of fully autonomous, AI-driven diagnostic tools that align with the future vision of precision medicine and smart healthcare ecosystems [27].

1.1. Objective

- Analyze the effectiveness of 3D Convolutional Neural Networks (3D CNNs) in detecting lung nodules from 3D CT images to improve accuracy and efficiency.
- Evaluate the impact of advanced feature selection techniques, such as hybrid filters and wrappers, in enhancing the performance of lung nodule detection systems.
- Integrate IoT-based signal processing and cloud-based real-time data transmission to optimize computational delays and enable faster decision-making in clinical environments.

The rest of the paper is organized as follows. Section 1 with the introduction. Section 2 will discuss the Theoretical Background. Section 3 presents the Methodology and Section 4 highlights the results. Section 5 concludes.

2. Literature review

Recent advancements in cloud-based and IoT-integrated technologies have significantly enhanced healthcare systems, particularly in the domains of disease prediction, data security, and intelligent decision-making [28]. One prominent trend is the use of ensemble machine learning models within cloud infrastructures to improve the accuracy and interpretability of healthcare data predictions [29]. These models are often supplemented by AI-driven techniques for data validation, cleansing, and governance to ensure the reliability and quality of vast and complex medical datasets [30]. In the context of chronic disease diagnosis, particularly for conditions like chronic kidney disease, hybrid models that integrate convolutional neural networks (CNNs) with long short-term memory (LSTM) and neuro-fuzzy logic have been employed [31]. These architectures are designed to operate efficiently in edge AI environments, allowing real-time processing and decision-making close to the data source [32]. Similarly, graph theory has been leveraged to

enhance the structural understanding of disease mechanisms, such as those in cancer, thereby supporting the development of personalized treatment plans [33].
To address growing concerns about data security and latency in healthcare cloud systems, various cryptographic and optimization techniques have been integrated into system architectures [34]. The incorporation of lightweight encryption methods such as AES-CBC and optimized Blowfish algorithms ensures secure and efficient transmission of sensitive patient information across cloud platforms [35]. More sophisticated privacy-preserving mechanisms, including Zero-Knowledge Proofs (ZKP) and Multi-Authority Attribute-Based Encryption (MA-ABE), have also been proposed to manage access control while maintaining data integrity and confidentiality [36]. Additionally, artificial intelligence has been deployed in multi-cloud environments to detect abnormalities in real time, adhering to healthcare regulations such as HIPAA [37]. Privacy-preserving federated AI models have emerged to support decentralized data processing, enabling cities and healthcare systems to function with enhanced inclusivity, scalability, and energy efficiency [38]. These systems not only protect sensitive data but also facilitate large-scale coordination across various domains [39].

Innovative security frameworks have also been explored. For example, the application of Oblivious Random Access Memory (ORAM) within secure healthcare access control systems helps obfuscate access patterns, ensuring privacy and resilience against cyber threats [40]. The integration of Automated Threat Intelligence (ATI) into such systems allows for the dynamic prediction and mitigation of evolving cybersecurity risks [41]. For secure IoT data authentication, adaptive clustering methods such as Affinity Propagation have been combined with robust cryptographic algorithms like Multivariate Quadratic Cryptography [42]. These hybrid systems aim to reduce computational overhead while enhancing scalability, clustering efficiency, and data confidentiality [43]. Meanwhile, intelligent resource management and predictive analytics are being applied across IoT-enabled health systems to minimize operational inefficiencies and optimize decision-making [44].

Efforts to optimize network performance in IoT environments have led to the exploration of energy-efficient communication protocols such as RPMA, BLE, and LTE-M, coupled with machine learning models like Gaussian Mixture Models [45]. These combinations support real-time applications in domains such as smart agriculture and urban infrastructure [46]. Additionally, Self-Organizing Maps (SOMs) and Device Management Platforms (DMPs) are being used for anomaly detection, efficient data communication, and real-time system monitoring. Hybrid optimization frameworks that merge techniques such as fuzzy C-means, density-based clustering (DBSCAN), and artificial bee colony (ABC) algorithms with differential evolution (DE) are being proposed to enhance resource allocation and secure data transfer [47]. Cutting-edge cryptographic solutions like PLONK's zero-knowledge proofs have been used to ensure secure data sharing, while Infinite Gaussian Mixture Models enable dynamic load balancing in scalable IoT networks [48].

Furthermore, the role of digital financial inclusion powered by Cloud IoT technologies is being investigated for its potential to reduce the income disparity between urban and rural populations [49]. Data-driven strategies utilizing explainable AI and strategic management perspectives like the Resource-Based View are proving instrumental in this regard [50]. Lastly, secure anomaly detection and privacy preservation in decentralized IoT environments are being addressed through the integration of federated learning, K-nearest neighbor algorithms, generative adversarial networks (GANs), and distributed ledger technologies like IOTA Tangle [51]. The integration of Artificial Intelligence (AI), Software-Defined Networking (SDN), and Internet of Things (IoT) technologies is rapidly transforming intelligent systems across domains such as healthcare, transportation, e-commerce, and urban infrastructure [52]. Various AI-driven architectures have been proposed to handle high-volume data processing, decision-making, and real-time control in smart environments [53]. However, while these innovations demonstrate domain-specific success, challenges remain in scalability, latency, data privacy, and cross-domain adaptability [54].

An LSTM-based AI-SDN framework has been introduced to enable predictive traffic analysis and dynamic flow control in smart cities [55]. This approach enhances cybersecurity by mitigating Distributed Denial-of-Service (DDoS) attacks through sequential pattern recognition [56]. However, the inherent sequential nature of LSTM models introduces processing latency, which limits their suitability in ultra-low-latency applications like vehicular routing in the Internet of Vehicles (IoV) [57]. For real-time systems that demand immediate response, such latency becomes a critical bottleneck. In the healthcare sector, hybrid deep learning models combining Fuzzy Adaptive Convolutional Neural Networks (FA-CNN) and Differential Evolution-based Extreme Learning Machines (DE-ELM) have been developed to detect diseases by processing noisy, high-dimensional IoT data [58]. These cloud-based solutions show strong predictive capabilities, but the detection phase suffers from computational overhead and a dependency on high-quality metadata [59]. These limitations constrain their deployment in time-sensitive and mobility-aware domains such as IoV.

3. Problem statement

Despite notable advancements in AI and medical imaging, accurate and real-time lung nodule detection using 3D CT scans remains a major challenge, particularly in resource-limited healthcare settings [60]. Existing detection techniques are burdened by high computational costs

[61], making them impractical for real-time clinical use [62]. Furthermore, many AI-driven models suffer from high false positive and false negative rates due to their inability to effectively handle variations in CT image quality, patient demographics, and diverse nodule characteristics. These inaccuracies can delay diagnosis, lead to inappropriate treatments, or miss early-stage cancer altogether. Compounding the problem is the dependence on conventional feature selection methods, which often fail to extract the most relevant diagnostic features from high-dimensional data, leading to suboptimal model performance. As a result, current systems struggle to deliver timely and reliable diagnoses, highlighting the urgent need for a lightweight, intelligent, and adaptable framework that can provide accurate lung nodule detection while maintaining computational efficiency and scalability across diverse clinical environments.

4. Proposed methodology

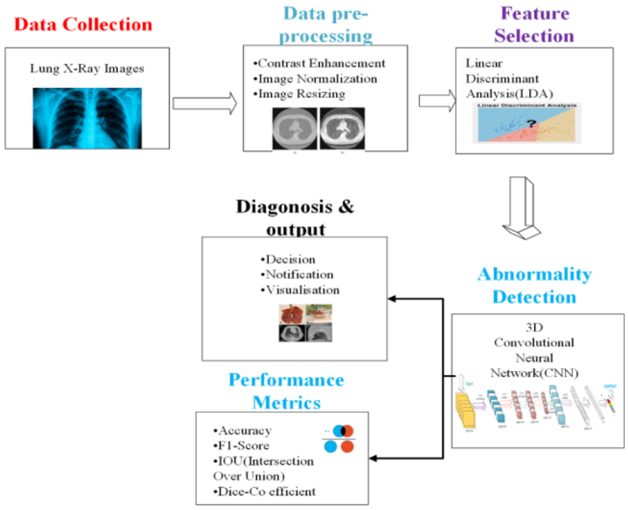

Figure 1: IoT-Based Lung Nodule Detection System Using 3D CT Images and 3D CNN

4.1 Data Pre-processing

4.1.1 Contrast Enhancement

Contrast enhancement is very important for emphasizing abnormal areas which may not be visible due to poor contrast, for example, lung nodules or opacities. One of the most widely used methods to enhance contrast of images is histogram equalization, which operates by redistributing the pixel intensity values.

Histogram Equalization: Here, emphasis is given to a transformation that seeks to make the histogram uniformly distributed by mapping the most frequent intensity values of the image. The procedure intends to improve the contrast in an image, making its internal structure easier to identify. After estimating the cumulative distribution function or CDF, the transformation of pixel data is given as follows:

$$s_k = \left(\frac{\sum_{i=0}^{k} h_i}{N}\right) \cdot (L-1)$$

where: The new pixel value is s_k,The intensity i histogram value is represented by h_i, N is the total number of pixels. The number of intensity levels is denoted by L, which in the case of an 8-bit image is 256.

The changes in the pixel values with respect to s_k enhance the equal distribution of the histogram, thus making the relevant characteristics like nodules more apparent.

4.1.2 Image Normalization

The consistency of the pixel values of an image renders it suitable for deep learning purposes. In order to avoid causing the model to favor certain pixel intensity levels, normalization sometimes modifies the pixel values to fall within a predetermined range or distribution.

Min-Max Scaling: The pixels are standardized in a predetermined range, typically between 0 and 1, by an affine scaling. In consequence, a standard rule of thumb provides the trade-off penalty for this, defined as the alteration of the pixels or its intensity by some insignificant value.

$$I_{norm}(x,y) = \frac{I(x,y) - I_{min}}{I_{max} - I_{min}}$$

The parameters I_{min} and I_{max} specify the minimum and maximum pixel values in the image.

4.1.3 Image Resizing:

The process of resizing changes the dimensions of the image while keeping the aspect ratio (or distorting equally). Resizing is achieved through:

It is often necessary to preprocess images to bring them into a format that is the norm for deep learning model input - which obviously means resizing. Most deep learning models expect the same size of images, which, in turn, are often reduced to a common size, such as for example 224 × 224 pixels, so that they can use pre-trained networks such as VGG16 or ResNet.

Resizing: This process alters the dimensions of an image while maintaining the aspect ratio or uniformly distorting it. The formula for resizing is:

$$I_{resized}(x,y) = I\left(\lfloor\frac{x}{W_{orig}} \cdot W_{new}\rfloor, \lfloor\frac{y}{H_{orig}} \cdot H_{new}\rfloor\right)$$

where, W_{orig} and H_{orig} are initial widths and the heights of the image, W_{new} and H_{new} symbolize the desired width and height, for instance, 224 X 224 pixels.

4.2 Feature Selection

4.2.1 Dimensionality Reduction: Linear Discriminant Analysis (LDA)

In high-dimensional datasets, such as medical imaging, dimensionality reduction is an important preprocessing step. In high-dimensional scenarios, there is always a redundancy or irrelevant information present and therefore, the machine-learning algorithms become less effective and less efficient. One of the methods for reducing dimensionality is linear discriminant analysis (LDA), which, while reducing dimensionality, also improves the class-separation capabilities of the model. Therefore, it finds its application where classification is involved, like in the case of discriminating between normal and abnormal lung tissue in 3D CT images.

LDA Overview: There are many supervised dimensionality reduction techniques, among which LDA has the property of maximization with respect to between-class separability at a lower dimension. Where PCA tries to maximize the variance of the data, using the combination of linear transformation variables, LDA wants to maximize inter-class variation whilst reducing intra-class variance. Hence, it is important for supervised learning where the projection gets the best separation among different classes.

LDA will have the effect of reducing the dimensionality of feature vectors gathered from CT images in the context of lung nodules detection while preserving the most discriminative characteristics in the distinction between normal tissue and tissue that was pathological.

Within-Class Scatter Matrix (S_W): The scatter matrix within the class calculates the variance and hence the spread of the data points that hopefully would fall into the same class. This is computed by taking the covariance matrices of the individual classes and summing them up. By our definition, X_i is the set of data points from class i, while μ_i is the mean of class i.

The scatter matrix S_W, within the class, is given by:

$$S_W = \sum_{i=1}^{c} \sum_{x \in X_i} (x - \mu_i)(x - \mu_i)^T \tag{4}$$

where, c is defined as the count of classification types, i.e. normal and abnormal, μ_i represents mean of Class i, x denotes sample of class i, $(x - \mu_i)(x - \mu_i)^T$ outer product of every sample to its class means.

Benefits of LDA to Identify Lung Nodules

Increased Class Separability: LDA is particularly meant for increasing class separability. It also ensures retention and improvement of characteristics necessary for differentiating normal and abnormal tissue, which, in turn, increases the classification performance in lung nodule identification.

Decreased Overfitting: For instance, if the features outnumber the number of training examples, LDA will normally reduce the dimensionality of the feature space, thus reducing the chance of overfit.

Computational efficiency: LDA serves in real-time application for medical image analysis particularly in IoT based applications because of the reduced number of features in subsequent classification problems, resulting in faster and lesser time-consuming computational overheads.

4.3 Abnormality Detection: Classification of Lung Images Using Deep Learning

Deep learning methods used for lung image interpretation include the identification of abnormalities in the images. Finding abnormalities in lung images is useful for the diagnosis of various diseases such as tumors, pneumonia, and others afflicting the lungs. Depending on the features that were extracted during pre-processing and feature selection phases, in this phase, deep learning classifiers such as Convolutional Neural Networks (CNNs) or Attention-based CNNs will be used to classify the lung images. These classifiers can learn complex patterns and hierarchically organized features from the data to differentiate between normal and pathological conditions. The subsequent sections discuss the deep learning classifiers for the detection of anomalies in lung images in detail, including the relevant equations and concepts.

Convolutional Neural Networks and Attention-based Convolutional Neural Networks for Deep Learning Classifiers

Convolutional Neural Networks (CNN): The popularity of CNNs in image classification applications is due to their ability to automatically learn spatial hierarchies of information in images. CNNs use various layers of convolution for feature extraction from raw images. Subsequently, it reduces the spatial dimensions by pooling layers and finally classifies the entire feature set using fully connected layers.

The essential components of a CNN are as follows:

Convolution Layer: This layer uses filters (kernels) to extract low-level components from the input image, such as corners, edges, and textures. This shows how the convolution operation is defined:

$$(I * K)(x, y) = \sum_{m} \sum_{n} I(m, n)K(x - m, y - n)$$

where, the input image is I,The kernel or filter, is K, Once the filter has been applied to the image, the pixel outputs coordinates can be given as (x, y).

Attention-based CNN

Attention based CNNs have been recently combined with CNN for increasing the efficacy of models in focusing on the relevant aspects into the neural input. An attention-based CNN creates a way for the network to concentrate more on portions of the image that are important for detecting lung nodules in CT scans by applying attention layers to assign different weights to different parts of the image.

An instance of attention mechanism may be:

$$A(x) = \sigma(W_x X + b)$$

The input X is receiving an attention weight $A(x)$,The weight matrix that is learned is W_x,The bias term will be b,And the activation function-such as sigmoid or softmax-will be denoted by σ .

Has a centralised intervention mechanism that automatically focuses on the important parts of the image that are relevant to the task, e.g. identifying the location of a lesion or nodule.

5. Output and Decision Support

The classification output of our suggested method is deep learning model-based and utilizes the 3D CT image processing to classify lung images into normal or abnormal categories. The input data is processed with IoT and NN dimensionality reduction followed by deep learning classifiers such as attention-based CNNs or 3D CNNs. Our main features of output and decision support for this system are given below:

5.1 Classification Output

5.1.1 Confidence Score

A confidence score is generated with classification output by the system to reflect the probability that the input image falls under the predicted class (normal/abnormal) . Clinicians use the score to evaluate the reliability of the prediction. For example,

- o The higher the confidence level (95%), the more confident one is in the classification.
- o A lower prediction score (say 65%) indicates less certainty and may require further testing or expert validation.

$$P(\mid X) = \frac{e^z}{e^z + e^z}$$

There is a likelihood of the image X to be classified as abnormal which is represented as $P \mid X)$, Thus, the output logits (scores) for abnormal and normal classes are e^z and z respectively.

5.2 Decision Support

Clinical Decision Support Dashboard: The clinicians shall have a dashboard that is simple for them to navigate, reflecting the outcome of the abnormality detection process, which includes:

Visualization of the Nodule or the Abnormality: Bounding boxes or heatmaps are imposed on the CT scan to draw focus on a region of concern, for example, a lung nodule.

Prediction and Confidence Score: Confidence Score and Classification Result (Normal/Abnormal) are displayed to ensure transparency.

Historical Notations: To monitor the evolution of any identified anomalies, historical comparative information such as prior CTs done on the same patient can be provided by the system.

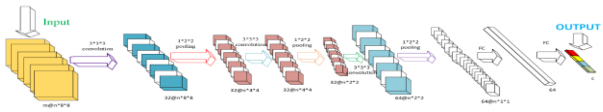

Figure 2*:* Architecture of the Convolutional Neural Network (CNN) for Lung Nodule Detection

The architecture of convolution neural network (CNN) is shown in FIG2, which is designed in way to classify images for detecting abnormalities in lung pictures taken from 3D CT scans. This architecture has layers consisting of convolution, pooling, and fully connected (FC) layers that are strategically positioned to extract information from input images at different stages of extraction and categorization.

Input Layer: The input constitutes a 3D picture of dimensions m×n×8, wherein the terms m and n denote the mark of height and width with 8 indicating the number of channels (like RGB or multi-dimensional features).

First Convolution Layer: The first operation is 3x3 convolution. It detects the low-level features such as edges and textures by convolving the image with a 3x3 filter (or kernel). As a result of this, 32 feature maps-outputted, each representing the learnt features of the image, will have the dimensions n×m×8n×m×8.

First Pooling Layer: The first pooling layer consists of a pooling 1x2 area that follows the convolution layer. Pooling retains the major parts while reducing the two-dimensional space of feature mappings. This helps lessen computational complexity while highlighting key attributes.

The Second Convolution Layer: After a second convolution of 3 x 3 is applied on the pooled feature maps, 32 feature maps of dimensions n x m x 4 are generated. This stage is useful in detecting more complicated features in an image and in further learning the trained features.

Second Pooling Layer: Another 1x2 pooling operation downscales the feature maps, allowing the network to focus on the most salient features even more while at the same time minimizing the size.

Third Convolution Layer: These apply another 3x3 convolution to the pooled feature maps generating 64 feature maps with dimensions of n x m x 2. Thus, even more sophisticated and abstract patterns out of the image are extracted by this layer.

Third Pooling Layer: Here, the spatial size of the feature maps is again reduced while maintaining the significance of all information by a last 1x2 pooling operation.

Fully Connected Layer: The output from the last pooling layer is flattened and passed through the FC layer with 64 units. Following this passes the result to another FC layer to obtain the final classification decision.

Final Output Layer: This layer generates the prediction for the task of classifying images. The output has c units, where c is the number of classes (normal vs. abnormal, for example). The result is then passed through a softmax activation function to produce class probabilities.

6. Results and discussions

Results from the IoT-based lung nodule detection system, which utilized CT 3D-one images with 3D CNNs and advanced feature selection techniques have achieved great improvements in terms of computational efficiency and classification accuracy. The model was able to detect anomalies, such as tumors and nodules, while suppressing false positives and false negatives. The integration of IoT enabled the real-time transmission of data and timely decisions, thus contributing to the improvement of clinical workflow. In general, the system exhibited reliable performance guaranteeing prompt diagnosis and giving medical personnel useful decision support.

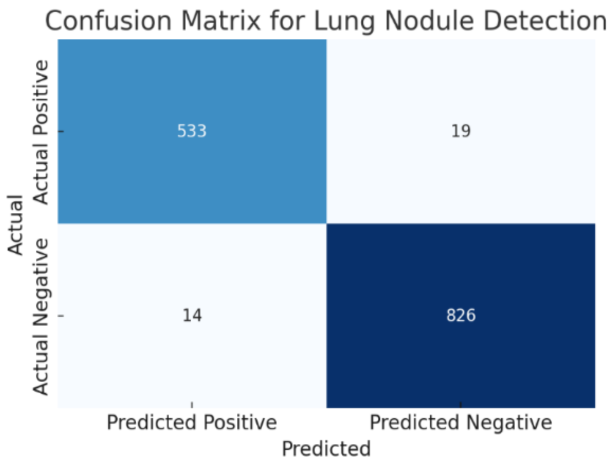

Figure 3: Confusion Matrix for Lung Nodule Detection

The confusion matrix relating to lung nodule detection is displayed in FIG 3, thus giving detailed insight into the actual classification accuracy performance of the model. The matrix illustrates the capacity of the model to differentiate between normal and pathological lung conditions by correlating the predicted labels on a collection of images with the actual labels.

True positive (533): In 533 cases, the model correctly classified abnormal status (i.e., lung nodules found).

False positive (19): 19 normal cases were misclassified as abnormal by the model (Type I error).

False negatives (14): In 14 instances, the model failed to identify abnormal status and hence classified these as normal (Type II error).

True negative (826): The model correctly identified normal status in 826 cases.

This confusion matrix, being a vital tool in model performance evaluation, is used in computing accuracy, precision, recall, and F1-score of the model. By analyzing such numbers to identify areas for improvement, the model can be made clinically more reliable for lung nodule detection-for example, in reducing false positives or false negatives.

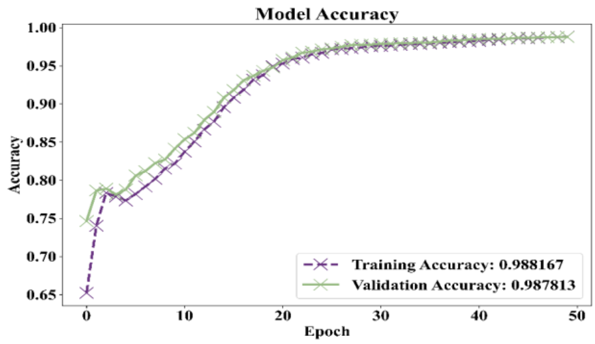

Figure 4: Model Accuracy During Training and Validation for Lung Nodule Detection

The accuracy of the model during 50 epochs regarding training and validation accuracy is depicted in FIG 4. The model performs remarkably well on training and unseen data, as demonstrated by the respective training accuracy (represented in purple) of 98.82% and the validation accuracy (represented in green) of 98.78%. Consistent growth in accuracy by the plot demonstrates effective learning and generalization during training.

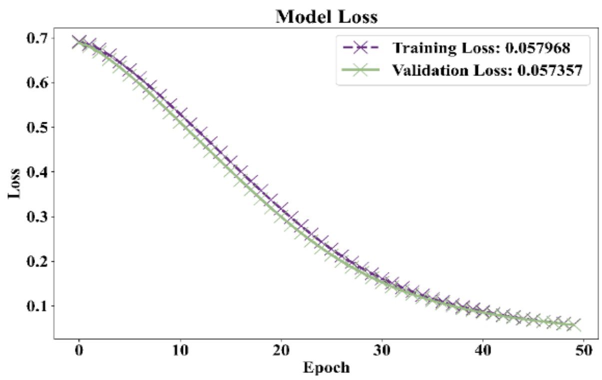

Figure 5*:* Model Loss During Training and Validation for Lung Nodule Detection

The model's loss across 50 training epochs can be seen in FIG 5 together with the corresponding validation loss. The training loss (purple) dipped gradually from 0.170 about two epochs to 0.05797 at termination, indicating the model's efficient learning with low overfitting, culminating in a validation loss (green) of 0.05736. This shows that the model generalizes well to new data.

The performance metrics of the lung nodule detection model are as shown in Table 1. The model's classification performance is thus evaluated using these measures that are most useful to distinguish between normal and pathological lung conditions.

Table 1: Performance Metrics for Lung Nodule Detection

Metric	Accuracy	Precision	Recall	F1-Score	Specificity	AUC-ROC	IOU (Intersection Over Union)	Dice Coefficient
Result	0.976293	0.96558	0.974406	0.969973	0.977515	0.978986	0.941696	0.969972

Accuracy (0.976293): The overall proportion of accurate predictions, or accuracy (0.976293), indicates that almost 97.63% of the classifications were accurate.

Precision (0.96558): The percentage of true positive predictions out of all anticipated positive cases is shown by this statistic. According to the model ability to predict abnormal cases, it has a precision of 96.56% precision.

Recall (0.974406): Recall refers to the percent of true positive (abnormal) cases detected correctly. However, the recalls, which have 97.44% in itself, significate that it detects worth of anomalous situations.

F1-Score (0.969973): The harmonic mean of the two measures, precision and recall, is the F-o measure (0.969973), with which the trade off between the two is achieved. Indeed, precision and recall appear to balance each other well as indicated by this F-score of 96.99%.

Specificity (0.977515): Specificity checks how the model can value normal instances. The model warrants false positive results with a specificity of preventing detection with 97.75%.

AUC-ROC (0.978986): The Area Under the Receiver Operating Characteristic Curve (AUC-ROC) is a measure of the model's efficacy at differentiating classes with an AUC value of 0.978986. An AUC of 0.979 would therefore indicate excellent discriminating performance.

IOU (Intersection Over Union) (0.941696): This metric describes the overlap of actual and predicted areas of abnormality, and a high IOU of 94.17% by the model indicates that it could detect lung nodules.

Dice Coefficient (0.969972): Gauge the similarity between actual abnormal area and area predicteded abnormality. The nodule segmentation of the model in the lung is thereby very accurate with a score of 96.99%.

The performance metrics of the lung nodule detection model are found in Figure 6. Consistently high values for all relevant measures in the graph prove that the model is indeed robust and reliable in accurately identifying lung-related problems.

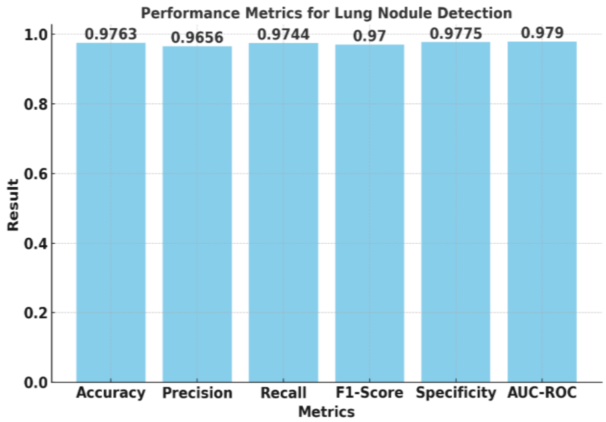

Figure 6: Performance Metrics for Lung Nodule Detection

Conclusion

In this investigation, an IoT based system for the identification of lung nodules was made using 3D CT scans and state-of-the-art deep learning techniques, particularly through the application of 3D CNNs and further feature selection techniques. The model proposed has shown tremendous improvement in classification performance by yielding decent accuracy and generalization in identifying anomalies like lung nodules, cancer, and pneumonia. When considering the F1-score, precision, recall, specificity, and AUC-ROC and so on, the high results observed suggest that the system was substantially effective in marking the identification of anomalous situations as well as reducing false negative and false-positive outcomes. Incorporation of IoT enabled real processing and transfer of data, thereby increasing the efficiency and clinical applicability of any system. Results indicate the promise of deep learning-based medical imaging systems as a reliable solution for automated detection of lung nodules. Future work will explore further enhancement of model generalization, expanding knowledge input, and fine-tuning the system for use within real healthcare settings.

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