IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

A HYBRID MODEL (hDCN) TO PREDICT LUNG CANCER FROM COMPUTED TOMOGRAPHY SCAN IMAGERY

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Abstract: One of the main causes of cancer-related mortality is lung cancer, which presents a serious healthcare issue. To address this issue, deep learning and AI technologies are being leveraged to enhance early detection and diagnosis. These innovative approaches analyze medical imaging data, such as CT scans, to improve accuracy and enable timely interventions, ultimately contributing to more effective and personalized treatments for lung cancer patients. Deep learning methodologies have been integrated to ascertain the presence of lung cancer in individuals by deriving relevant characteristics from CT-Scan images sourced from a data repository. These predictive systems not only identify lung cancer but also facilitate the analysis of inherent behavioral patterns within the images, offering additional insights. This study looks into how machine learning (ML), deep learning (DL), and artificial intelligence (AI) can improve lung cancer diagnosis, particularly through the analysis of medical imaging data, such as CT scans and by doing so focuses on a method for more precise early detection for lung cancer. In doing so this research paper proposes a novel algorithm, the Hybrid Deep Neural Network-Convolutional Neural Network (hDCN). Evaluation through standard statistical techniques reveals an accuracy rate of 69.024% and an impressive precision of 94%, highlighting the hDCN algorithm's potential in transforming early detection strategies for lung cancer.

Index Terms – Convolutional Neural Network, Deep Learning, Deep Neural Networks, Lung Cancer

I. INTRODUCTION

Lung cancer remains one of the most prevalent and lethal forms of cancer worldwide, posing a significant challenge to early detection and effective treatment. There has been a paradigm change toward the incorporation of modern technologies, including machine learning (ML) and deep learning (DL), due to the pressing need to improve screening procedures and diagnosis accuracy. This essay delves into the current landscape of lung cancer detection, highlighting the crucial role of ML and DL in revolutionizing diagnostic approaches. It also explores the limitations of existing methods, thereby emphasizing the need for more effective techniques.

Early-stage symptoms of lung cancer, which is defined by unchecked cell development in the lung tissues, are frequently vague, which leads to late-stage diagnosis and few therapeutic choices. The conventional diagnostic methods, such as X-rays and CT scans, have proven valuable but are not without limitations. These modalities may not detect small lesions or early-stage tumors, leading to delayed interventions and decreased survival rates.

Machine learning has become a viable solution to many problems in recent years. Large-scale dataset analysis, pattern recognition, and prediction based on learnt characteristics are all possible using machine learning algorithms. This is particularly valuable in the realm of medical imaging, where early detection can significantly impact patient outcomes. Various ML techniques, ranging from classical methods like support vector machines to more sophisticated ensemble models, have been applied to lung cancer detection with notable success.

Deep learning is a branch of machine learning (ML) that uses neural networks to mimic the functioning of the human brain. It has attracted a lot of interest due to its remarkable image recognition ability. One kind of deep learning architecture called Convolutional Neural Networks (CNNs) has shown amazing accuracy in identifying anomalies in medical pictures, such as those that show lung cancer. DL algorithms excel at learning hierarchical representations of data, enabling them to discern intricate patterns and subtle abnormalities in radiological images that might elude traditional methods.

The incorporation of DL into lung cancer detection methodologies signifies a quantum leap in diagnostic capabilities. DL algorithms exhibit superior sensitivity and specificity, enabling them to identify minute lesions and classify abnormalities with a level of precision unmatched by previous techniques. As a result, there is a growing body of research advocating for the integration of DL into routine clinical practices for lung cancer screening and diagnosis.

Despite the progress made with ML and DL, there exist challenges that necessitate the development of more effective methods. False positives and false negatives remain concerns, potentially leading to unnecessary interventions or overlooking critical cases. Moreover, the interpretability of DL models poses a challenge, as the complexity of neural networks makes it difficult to elucidate the rationale behind their predictions. Addressing these issues requires a concerted effort to refine existing algorithms and develop novel methodologies.

The need for more effective lung cancer detection methods is underscored by the evolving landscape of healthcare and the increasing demand for personalized medicine. Early detection not only improves treatment outcomes but also reduces healthcare costs associated with advanced-stage interventions. These objectives may be met in large part by machine learning, and deep learning in particular, which can provide precise, effective, and understandable lung cancer detection systems.

Several variables are driving the trend in the application of deep learning in lung cancer diagnosis. First off, training sophisticated deep learning models has never been easier because to the wealth of medical imaging data and advances in computing power. The scalability of deep learning algorithms allows them to harness vast amounts of data, learning intricate patterns that may elude traditional algorithms. DL is positioned as a powerful tool in the search for more precise and trustworthy lung cancer diagnosis because to its data-driven methodology.

Secondly, the adaptability of deep learning models to diverse data types contributes to their effectiveness in integrating multiple modalities for comprehensive lung cancer assessment. While traditional methods often focus on a single imaging modality, DL has demonstrated the ability to fuse information from various sources, such as CT scans, X-rays, and even clinical data, to enhance diagnostic accuracy. This integrative approach aligns with the holistic nature of healthcare and facilitates a more comprehensive understanding of individual cases.

Furthermore, the ongoing research and development in DL architectures, such as recurrent neural networks (RNNs) and attention mechanisms, are refining the capabilities of these models. RNNs, for instance, are well-suited for sequential data, allowing them to capture temporal patterns in medical images, which is crucial for monitoring changes in lung tissues over time. Attention mechanisms enable models to focus on specific regions of interest, mimicking the selective attention employed by radiologists during manual image analysis.

So the detection of lung cancer has entered a transformative era marked by the integration of machine learning, particularly deep learning, into diagnostic methodologies. While existing approaches have shown promise, the imperative for more effective methods persists due to the inherent challenges and complexities of lung cancer diagnosis. Deep learning's ability to process large amounts of data, include many modalities, and adjust to changing research and development is what drives its advancement. The integration of technology innovations and clinical knowledge is crucial for opening up new avenues in the early identification and treatment of lung cancer as the area develops.

II. RELATED WORK

This research addresses the imperative for timely lung cancer diagnosis through the implementation of a sophisticated 3D-CNN and RNN algorithm. Leveraging the LUNA 16 database, the study introduces an novel method for extracting features from CT scan pictures. The proposed hybrid deep learning method demonstrates significant promise, achieving a notable 90% selectivity, 87% sensitivity, and 95% accuracy. These results highlight the created model's potential to improve lung cancer detection efficiency and accuracy, making significant contributions to early diagnostic programs [1].

The study report offers a state-of-the-art deep learning model created especially to forecast PD-L1 expression in patients with non-small-cell lung cancer. By leveraging enhanced chest CT images, this model offers the potential to revolutionize personalized treatment strategies, making them more precise and effective for patients [2]. This study looks into a color-based deep learning technique for lung cancer tissue slide classification. By using color-based features in deep learning models, this method shows great promise for efficiently and accurately assessing lung cancer pathology, potentially enhancing the accuracy of disease diagnosis and prognosis[3].

This study explores the use of deep learning methods to the interpretation of CT scan and histopathological image data in order to predict lung cancer. By providing insightful information on the use of sophisticated picture analysis, this method increases the possibility of early illness detection and individualized treatment planning [4]. The study investigates an automated decision support system for the identification and categorization of lung cancer. For increased accuracy, it makes use of a multilayer fusion Region Proposal Network (RPN) in conjunction with an augmented Region-based Fully Convolutional Network (RFCN). The suggested methodology shows encouraging outcomes in the detection of lung cancer[5].

Deep learning algorithms are commonly deployed in isolation, tailored for specific tasks. In contrast, transfer learning seeks to utilize knowledge gained from addressing one problem to address others, as opposed to traditional training models developed independently. The suggested technique extracts pictures with features by using Convolutional Neural Network (CNN) models that have already been trained. These structures are then sent into a fully connected layer that uses standard pooling to classify molecules as benign or harmful. The proposed system presents a novel method for identifying breast tumors by utilizing Balance Contrast Enhancing Technologies (BCET) to improve characteristics and extract features from medical pictures for precise diagnosis.[6]

The suggested method employs shape-based attributes for tumour cell identification. Furthermore, these characteristics are utilized for categorizing cells as either healthy or cancerous through Naive Bayesian and ANN. One essential component that the suggested framework addresses is the rating of the impacted cells, which makes it easier to evaluate important patient care practices during clinical assessments. Experiments using patient data obtained from pathologists are carried out to demonstrate the efficacy of this methodology. [7]

This research provides a comprehensive analysis of lung cancer using deep learning approaches. By carefully examining articles from various conferences and publications using searches on databases including ScienceDirect, IEEE Xplore, Springer Link, Google Scholar, and Wiley, the authors conducted an evaluation of the literature. The efficacy of many methods and procedures for recognizing lung cancer cells was assessed after an examination of their system design structures [8]. In this paper, a combined fusion method based on an adaptive sparse representation integrated into a Laplacian pyramid (LP) decomposition is presented. Its success stems from its capacity to classify into various forms; segmented sizes were combined into four layers by means of the LP approach. An approximation of 0.99% was obtained by computing the Dice Similarity Coefficient (DSC), a performance metric that was employed in the model assessment process using a dataset[9].

The researchers created a machine for swift lung cancer detection through a manual approach. Their dataset included 1800 photos, including 900 of children with lung cancer diagnoses, CT scans, and a Gabor filter. Unfortunately, the publishers did not provide information about how successful their method was. In contrast, they also devised a Computer-Aided Diagnosis (CAD) model, subjected to testing on three datasets. It had an accuracy of 99.42% on average and 99.61% at its highest point. Interestingly, the CAD model produced results of 99.76%, 99%, and 99%, respectively, indicating high F-score, recall, and accuracy [10]. A machine learning

(ML) model was developed in reference [12] to evaluate the risk of lung cancer in a sizable group of younger patients. The model exhibited effectiveness by accurately pinpointing a high-risk segment constituting 10% of individuals diagnosed with lung cancer. While the model is available for broad distribution and application, it is crucial to acknowledge the necessity of addressing racial variations when employing ML techniques.

In order to identify lung cancer in its early stages, the authors of [13] recommend using machine learning (ML) approaches, namely the Nave Bayes (NB) and SVM classification algorithms. The research highlights the need of prompt diagnosis and investigates the possibility of machine learning to comprehend disease patterns. A comparative analysis of the accuracy of both systems is presented, providing valuable insights for prospective research in the field. The researchers in [14] describe an inquiry into the development of prediction models for the survival and recurrence of patients with lung adenocarcinoma and squamous cell carcinoma using genetic, clinical, and demographic data. Three machine learning algorithms—decision tree approaches, neural networks, and support vector machines—are compared for accuracy and benefits in this study. The findings show that although decision tree models might not result in a significant improvement in accuracy, they do a good job of highlighting the most important variables in the input data. This capability enables healthcare professionals to make more personalized decisions for the benefit of the patients.

In the study documented in [15], the author validates the application of CXR-LC, a freely accessible deep learning (DL) tool, to pinpoint individuals at an increased risk for lung cancer screening by analysing electronic medical record (EMR) data. CXR-LC proved useful in detecting people at high risk for lung cancer, including those who were considered unsuitable by the most recent CMS guidelines. Adoption of CXR-LC may increase screening uptake and maybe lower lung cancer death rates. The authors of reference [16] present Sybil, a novel deep learning (DL) model that uses a single low-dose computed tomography (LDCT) scan to predict a person's future risk of acquiring lung cancer without the need for further clinical or demographic information. The model demonstrates commendable accuracy in external validation sets, suggesting its potential for personalized screening. However, further investigation is warranted to comprehensively grasp its clinical applications.

A continuous monitoring method is suggested by the authors in [17] for the creation of lung cancer prediction models. They use fuzzy cluster-linked augmentation combined with a classification algorithm. In this technique, the fuzzy clustering method is considered necessary to provide accurate picture segmentation. This strategic combination aims to enhance the accuracy of lung cancer prediction through continuous monitoring, emphasizing the pivotal role of fuzzy clustering in achieving meticulous image segmentation for more robust modelling. In the work reported in [18], cutting-edge deep learning (DL) techniques are used to conduct a thorough investigation of lung cancer cells. Given the profound impact of lung cancer on mortality rates, in-depth investigations are imperative for a nuanced understanding. The utilization of computed tomography (CT) scan images emerges as a sophisticated diagnostic avenue, enabling the estimation of the probability of an individual developing lung cancer. Notably, the identification of nodules, indicative of early tissue development, serves as a pivotal element in unravelling the intricate landscape of lung cancer progression within the existing literature

Within the framework of [19], researchers incorporated a combination of CNN and RNN. By leveraging CT scan images captured both pre and post radiation therapy, their CNN model was trained to prognosticate survival outcomes. This study made it possible to monitor tumours continuously, which made it possible to forecast survival and prognosis at one- and two-year markers for overall survival. This study's use of enhanced models represented a substantial improvement in the prediction power of the disease's progression and patient outcomes. The author of the paper described in [20] provides a thorough examination of lung cancer and freely available benchmark datasets to support robust scientific inquiry. The examination extends to current research endeavours utilizing sophisticated deep learning (DL) algorithms for the meticulous analysis of medical images related to lung cancer. The study's concluding remarks, which cover a variety of detection and classification methodologies, highlight the critical roles that clinical advancements, technological innovations, and anticipated future developments play within this crucial domain. As such, they provide insightful information that will continue to advance the field of lung cancer research.

The study conducted in [21] employed a deep learning (DL) methodology, employing the U-Net and ResNet34 architectures in particular. Four different datasets were used to assess the system's effectiveness, and the Dice Similarity Coefficient (DSC), an assessment parameter, exceeded 0.93. Notably, a meticulous examination involving two pathologist instances revealed a subtle reduction in consolidation. This paper illustrates an exemplary technique demonstrating F-scores ranging from 99.2% to 99.3%. The recommended approach, utilizing success metrics, provides a comprehensive assessment of the condition, exemplifying its proficiency in achieving consistently high F-scores.

III. SYSTEM ARCHITECTURE

The proposed system architecture for Utilizing Deep Neural Networks to Predict Lung Cancer from CT Scan Imagery utilizes Hybrid Deep Neural Network-Convolutional Neural Network(HDCN) to address the unique challenges faced to improve the existing systems that are used for detection . Deep learning and transfer learning have been transformative in their ability to efficiently handle diverse data types. In line with this, we've embraced the same concept by adopting a deep learning model, specifically the Convolutional Neural Network (CNN), enhanced through the integration of Deep Neural Network (DNN) methods. The CNN leverages filters in its convolutional layers, with each filter designed to identify and extract features from input images, subsequently transferring this knowledge to other layers for further processing. The number of filters in a convolutional layer can vary depending on the data under consideration, as these filters essentially serve as feature detectors in the input data.

The capabilities of CNN and DNN approaches are smoothly combined in the suggested system architecture to provide reliable lung cancer diagnosis. Convolution layers, max pooling, and one or more fully connected layers are among the layers that are integrated in this way to form the basic structure of the CNN component. The dataset is stratified into three subsets: a training set (seventy percent), a testing set (twenty percent), and a validation set (ten percent). During the training phase, the CNN component, enriched with layers such as Convolutional, Maxpooling, and Fully Connected layers, undergoes a comprehensive learning process. This involves the utilization of convolutional layers as extractors to learn representations of image pixels. The convolutional filters play a pivotal role in creating information maps from neurons, where each feature map is denoted by * . The efficiency functionality map is improved by the 2D convolution layers, shown by, which measure the internal result of filtration in each feature of the input image. Nonlinear features, denoted by Eq. (1), are applied through activation functions (f) to the input image (X), offering increased abstraction.

$$C_{\mathrm{o}} = f(f_m \times X) \qquad (1)$$

Convolutional layers not only aid in spatial normalization to input rotations and deformations but also reduce spatial granularity through common pooling levels. The resulting output from the convolutional layer, denoted by Eq. (2), represents the culmination of features from all input mappings.

$$\mathrm{C}_{\mathrm{o}}^{\mathrm{CL}} = f(\prod_{\mathrm{i}=0}^{\mathrm{N}} \mathrm{C}_{\mathrm{i}}^{\mathrm{CL}-1} \times KN_i^{CL} + \prod_{j=0}^{M} AB_j^{CL}\ ) \qquad (2)$$

The testing subset, constituting 20% of the dataset, evaluates the generalization capability of the CNN model. The integrated layers, including convolution and pooling, contribute to precise pattern recognition, ensuring robust performance on new, unseen data.
The remaining 10% of the dataset is reserved for the validation phase. Here, the intricate layers collectively fine-tune the CNN model, ensuring its adaptability and reliability in real-world scenarios. Complementing the convolutional layer, the flattening process efficiently transitions from the CNN's output to the subsequent Dense DNN layer. This critical step allows for the generation of probabilities for the predicted values. Throughout the entire process, model evaluation includes key metrics such as accuracy and precision. The comprehensive layer architecture facilitates iterative optimization, enabling adjustments to hyperparameters and model structures to enhance overall performance

Our neural network's depth is increased when DNN techniques are incorporated into the model, enabling more complex feature extraction and learning. This depth eventually contributes to greater accuracy by improving the model's capacity to capture intricate patterns in the data.

3.1 Components of CNN

The cornerstone of the architecture, the CNN layer employs adaptive convolutional filters to discern features from input images. This pivotal component adapts its filter count for dataset-specific feature detection. The 2D convolution layers, denoted by * , capture intricate features through inner filtration outcomes, enhancing efficiency functionality maps for Co, as per Eq. (1). Following CNN, the Maxpooling layer down samples feature maps, reducing spatial dimensions and computational complexity.

Activation functions like ReLU (Rectified Linear Unit) are applied to introduce non-linearity into the model. This non-linearity allows our architecture to model complex relationships within the data. This layer enhances training stability by normalizing input, mitigating challenges like vanishing gradients during training. To prevent overfitting, a Dropout layer is incorporated, which randomly deactivates a percentage of neurons during training, enhancing model generalization.

3.2 Components of DNN

The output from the preceding layers is flattened to create a one-dimensional vector, preparing it for input into the DNN layer. A deep neural network layer receives the flattened data after which it processes it for more intricate data analysis and pattern detection. Finally, the DNN layer provides the probability of the predicted value, making this architecture suitable for image classification tasks where accuracy is of paramount importance.

Combining CNN with DNN techniques yields a reliable and accurate model that performs better on tasks like object identification and picture categorization. By deeply integrating DNN techniques, our model excels in capturing intricate data representations, which significantly contributes to its improved accuracy and precision and predictive capabilities.

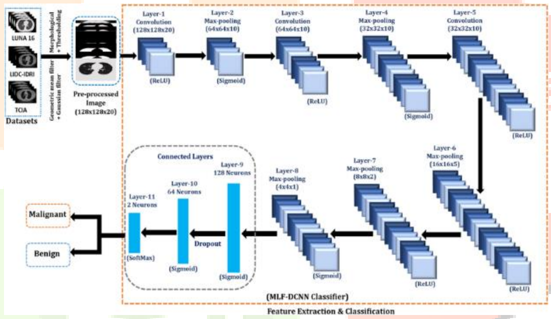
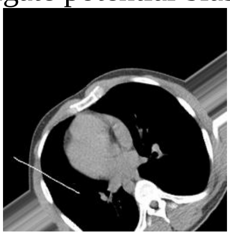


Figure. 1 Hybrid Frame work [22]

IV. EXPERIMENTS AND RESULTS

The data utilized in this research was sourced from a reliable Kaggle data repository, emphasizing the significance of data quality and credibility. In preparation for model training, an extensive pre-processing and cleaning protocol was implemented to eradicate potential biases inherent in the dataset. To further optimize the model's performance, various data augmentation techniques were employed, contributing to a more robust and versatile training set. Following these preprocessing steps, the dataset was meticulously organized into two separate folders: one housing 'normal' images and the other 'not normal' images. Each of these folders encompassed an extensive collection of over 1500 images. To maintain consistency and facilitate effective model training and evaluation, all images were uniformly resized to a resolution of 255 x 255 pixels in RGB format. This standardization ensures that the model encounters a consistent input format throughout the training process, thereby promoting accurate learning and evaluation. It is imperative to note that these measures were taken to mitigate potential biases and enhance the overall reliability of the study's findings.



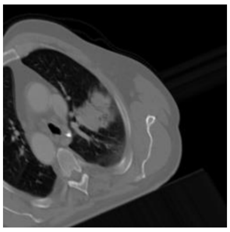


Figure 2 Normal Image Figure 3 Abnormal Image

Choosing the right assessment metric is crucial for evaluating the effectiveness of our lung cancer prediction algorithm. Since our task involves binary classification using a neural network, we opt for the binary cross-entropy (log loss) metric.

Binary Cross-Entropy (Log Loss): The model's performance in binary classification tasks is assessed using a measure called binary cross-entropy, which is sometimes referred to as log loss. It measures how different the real class labels are from the probabilities that were anticipated.

Calculation Process: The binary cross-entropy metric is computed by first correcting the predicted probabilities. This correction involves subtracting the probability of a data point belonging to class 1 from 1 (e.g., for a data point like ID8, which belongs to class 0 but has a predicted probability of 0.56, we compute the corrected probability as 1 - 0.56 = 0.44).

Log Transformation: Subsequently, a log transformation is applied to each of the calculated corrected probabilities. This transformation helps in penalizing misclassifications and assessing the model's confidence in its predictions.

Average of Negative Corrected Probabilities: To obtain the final log loss (binary cross-entropy) value, the average of the negative corrected probabilities is calculated. The model performs better in lung cancer prediction the smaller the resulting log loss value.

Interpretation: When the model's predictions are more closely aligned with the actual class labels, the log loss value decreases, indicating a more precise and dependable prediction. It is a critical metric for evaluating the quality of our lung cancer prediction model.

The study yielded compelling results, firmly establishing the Hybrid Deep Neural Network-Convolutional Neural Network(HDCN) as a highly effective model for lung cancer identification. Notably, the HDCN demonstrated a remarkable accuracy rate of 69.024%, surpassing the performance of traditional Convolutional Neural Networks (CNN). This outcome underscores the HDCN's superior ability to discern complex patterns within medical images, a critical factor in accurate lung cancer detection.

Of particular significance is the precision metric, where the HDCN excelled with a precision rate of 94%. This metric reflects the model's capacity to minimize false positives, signifying its precision in correctly identifying instances of lung cancer. The high precision value attests to the HDCN's reliability in clinical applications, crucial for minimizing diagnostic errors and enhancing patient outcomes.

These results are not merely indicative of the HDCN's superior accuracy but also highlight its potential for practical implementation in real-world scenarios. The incorporation of rigorous evaluation metrics, such as precision and accuracy, provides a comprehensive understanding of the HDCN's robust performance. The findings collectively signify a notable advancement in lung cancer detection methodologies, positioning the HDCN as a promising tool for improving the accuracy and reliability of diagnostic processes in the realm of medical imaging.

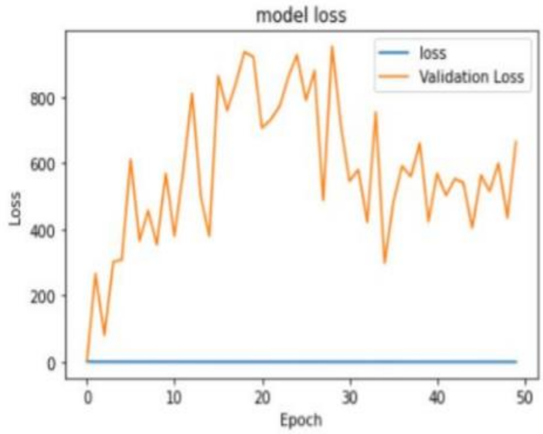


Figure 4 Loss value of HDCN

In comparison to existing works with data taken from our literature reviews, our hybrid Deep Neural Network-Convolutional Neural Network (hDCN) model outperforms both traditional Convolutional Neural Network (CNN) and Deep Neural Network (DNN) approaches in terms of accuracy and precision. The hDCN model achieves a significantly higher accuracy of 69.024%, surpassing CNN (65%) and DNN (62%). Moreover, the precision of our hDCN model stands at an impressive 94%, showcasing its superior capability for accurate lung cancer detection compared to CNN (58%) and DNN (48%). These advancements highlight the effectiveness of our hybrid model in enhancing both accuracy and precision over existing methodologies.

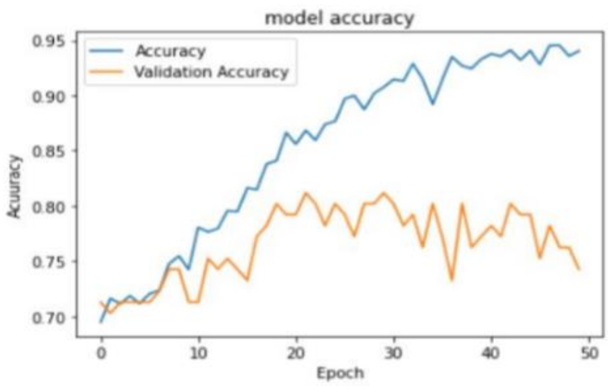


Figure 5 Accuracy Measure of HDCN

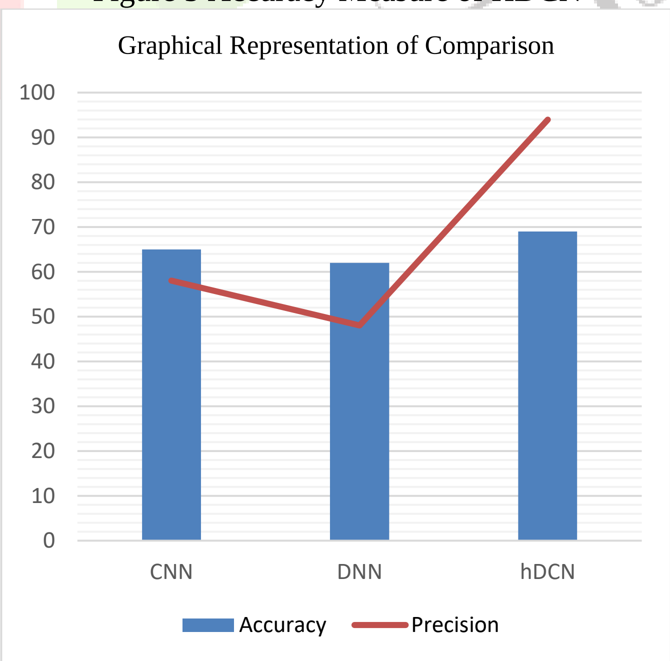


Figure 6. Comparison with existing models

V. CONCLUSION AND FUTURE WORK

The proposed Hybrid Deep Neural Network-Convolutional Neural Network(HDCN) architecture, blending Convolutional Neural Networks (CNN) with Deep Neural Network (DNN) methods, presents a formidable framework for image classification, with a particular focus on early lung cancer detection. By synergistically combining CNN's feature extraction capabilities with DNN's depth and complexity, the architecture attains a heightened level of performance in precision . Incorporating evaluation metrics, such as binary cross-entropy (log loss), is pivotal. This metric provides a quantitative assessment of the model's predictive accuracy, with a lower log loss indicating a better-performing model. The HDCN architecture, along with meticulous metric selection, not only enables more precise predictions but also improves the reliability and generalization of the model. This architecture, characterized by its enhanced depth and comprehensive understanding of evaluation metrics, stands poised to significantly elevate the accuracy and efficacy of image classification tasks, thereby proving very valuable in fields such as medical image analysis and beyond.

Subsequent research in the field of lung cancer detection may investigate the synergistic fusion of several deep learning techniques, including generative adversarial networks (GANs), recurrent neural networks (RNNs), and convolutional neural networks (CNNs). Integrating these diverse architectures can potentially enhance accuracy and precision by capturing complementary features and patterns in medical imaging data. Additionally, exploring ensemble techniques that combine predictions from multiple models, including traditional machine learning algorithms, could further optimize performance. Investigating transfer learning strategies, where pre-trained models are adapted for specific tasks, offers avenues to leverage knowledge from diverse datasets. Implementing advanced data augmentation methods and exploring the impact of attention mechanisms in deep learning models are promising avenues for refining accuracy and precision in lung cancer detection. Collaborative research endeavours focusing on innovative combinations of deep learning techniques can pave the way for more effective and reliable diagnostic tools.

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