Enhancing Lung Tumor Classification Accuracy: A Deep Feature Fusion Approach with Robust Framework Validation

Abdulmohsen Algarni[*], Ali Hamza[**], Muhammad Anas[***] Muhammad Assam[****]

[*] Department of Computer Science, King Khalid University, Abha 61421, Saudi Arabia
[**] Department of Mechatronics Engineering, University of Engineering & Technology Peshawar, Pakistan
[***] Department of Electrical & Electronics Engineering, Swinburne university of Technology Hawthorn Campus.
[****] Department of Software Engineering, University of Science and Technology Bannu KP Pakistan

Abstract- Lung cancer is a widespread and deadly kind of cancer that has a high death rate globally. Conventional diagnostic techniques that rely on visual examination by healthcare professionals are susceptible to mistakes and are time-consuming because of the similarities between tumours. This paper presents a new strategy for classifying lung tumours using a deep feature fusion technique. At first, deep features are obtained from Computer Tomography (CT) images using various Convolutional Neural Network (CNN) structures such as ResNet18, ResNet50, Alex-Net, and DenseNet201. These features are classified using Support Vector Machines, K-Nearest Neighbors, Linear Discriminant, and Naïve Bayes. The highest-performing separate feature vectors, specifically ResNet50 and DenseNet201, are combined to construct a discriminative and informative fused feature vector. The proposed vector demonstrates a substantial increase in accuracy (95%) when compared to separate vectors. In addition, we assess the effectiveness of our strategy by comparing it to other advanced techniques, showcasing its resilience in classifying lung tumors. This approach shows potential for early illness diagnosis by healthcare experts.

Index Terms- Feature fusion, Deep learning, Machine learning, Nedical image diagnosis and Lung Cancer.

I. Introduction

Lung Lung cancer is a prominent cause of cancer-related fatalities globally, posing a substantial challenge in both industrialized and developing nations. Non-small cell lung cancer (NSCLC), the most common kind, exhibits a mere 18% 5-year survival rate due to its frequent diagnosis in advanced stages and its restricted treatment alternatives [1,2]. Due to the limited improvement in survival rates for lung cancer, it is essential to regularly observe changes in radiographic tumours and treatment responses in order to achieve more effective results.

Current clinical response evaluation criteria, such as RECIST [3], employ simple metrics based on size to analyse changes in tumour dynamics over time. The latest progress in deep learning has created new opportunities for automated image analysis, removing the requirement for manual selection of features [4]. Convolutional neural networks (CNNs) excel at autonomously extracting intricate visual characteristics and discerning non-linear connections within extensive datasets [5,6]. Consequently, they serve as a significant instrument for evaluating medical imaging and ascertaining the stage of malignancies.

Radiologists are faced with the challenging and time-critical task of precisely detecting cancerous lung lesions using computed tomography (CT) imaging. Computer-aided diagnostic (CAD) [7] systems have been created to tackle this problem. However, conventional machine learning (ML) methods face challenges in achieving the highest level of accuracy because they require manual extraction of features. Conversely, deep learning (DL) approaches have demonstrated their transformative impact by exhibiting outstanding performance across various domains [8].

We describe a state-of-the-art, fully automated system for classifying lung tumours. This method employs modern techniques for extracting and combining deep features. By employing sophisticated deep learning algorithms, our methodology aims to enhance the precision and effectiveness of diagnoses. This offers healthcare providers a crucial instrument for swiftly recognizing and managing instances of lung cancer. The suggested study presents numerous significant contributions to the field:

Initially, deep Convolutional Neural Network (CNN) features were obtained from four distinct architectures: Alex-Net, Dense Net, Res-Net 18, and ResNet50. This facilitated a comprehensive examination of feature representation. Subsequently, we employed a cutting-edge technique to merge the most efficient characteristics into a unified vector, leading to enhanced discriminatory capability and robustness in contrast to individual vectors. The combined feature vector was subjected to classification using Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Linear Discriminant (LD), and Naïve Bayes (NB) methods, yielding a remarkable accuracy rate of 95%.

The paper is structured as follows in the subsequent sections: Section II provides a comprehensive analysis of the existing literature, offering a precise comprehension of the current research in the topic. Section III delineates the proposed technique, offering an elaborate elucidation of the feature extraction, fusion, and classification procedure. Section IV contains the outcomes of our trials, encompassing performance measures and comparative analysis. Finally, Section V offers conclusive thoughts and emphasizes prospective avenues for future research.

II. Literature Review

Deep learning approaches are now being investigated by researchers in the field of lung cancer diagnosis in order to improve the efficiency of computer-aided diagnosis (CAD) systems. By utilizing their capacity to learn nuanced patterns from complicated, layered, and hierarchical data structures, deep learning models demonstrate higher performance in comparison to standard Machine Learning (ML) approaches. These models are inspired by the intricate workings of the human brain. The implementation of deep learning algorithms was mostly linked with straightforward tasks such as picture classification ten years ago. However, recent improvements have proved that these algorithms are effective in solving increasingly complex classification difficulties.

For example, Chaunzawa et al. [11] suggested a method for classifying lung tumours that made use of machine learning techniques. They were able to achieve a remarkable Area Under Curve (AUC) value of 0.71. In a similar manner, Singh et al. [12] utilized Multi-Layer Perceptron (MLP) for the categorization of lung tumours, and they were fortunate enough to achieve an accuracy of 88%. [13] Bhatia and colleagues built an automated system that made use of U-Net architecture, and they were able to achieve an impressive accuracy of 84%. Using features taken from Zernike's moments, Gabor features, Tamura texture features, and the Grey Level Co-occurrence Matrix (GLCM), Gupta et al. [14] addressed the diagnosis of Chronic Obstructive Pulmonary Disease (COPD) and Fibrosis. This was accomplished by utilizing the aforementioned characteristics. Following that, classification was carried out with the assistance of a number of different methods, such as k-Nearest Neighbor (KNN), Support Vector Machine (SVM), Random Forest Classifier, and Decision Tree Classifier. Both of these approaches were utilized.

In addition, Joshua et al. [15] presented a 3D Convolutional Neural Network (CNN) unsupervised learning model for lung cancer diagnosis. This model made use of a binary classifier technique and was referred to as 3D CNN. When it comes to improving the visibility of lung tumours, this model has shown some rather encouraging outcomes. To diagnose lung cancer, Qin et al. [17] created a hybrid network model that was based on the CNN-RNN architecture. This model made it possible to extract, analyze, and combine multitype interdependent variables to ascertain the status of an EGFR mutation.

Deep learning (DL) was utilized in the multilayer multimodal fusion system that was built by Agarwal et al. [18]. The system's primary objective was to identify diseases within the population. Their strategy required discriminative data from all levels to achieve a higher level of detection accuracy. Behrad and Abadeh [19] explored a variety of learning strategies, including end-to-end, multitask, and transfer learning, in addition to discussing common deep learning models and multi-modal fusion approaches. In addition to providing insights into various learning approaches, they provided a summary of the DL method for the analysis of multi-modal medical data. A powerful deep learning model for anatomical design in chest radiographs was presented by Ullah et al. [20]. This model was developed with the help of a dual encoded-decoded Convolutional Neural Network (CNN). The power of the network's representation was increased through the utilization of a pre-trained encoded outcome, which was a squeeze-and-excitation (SE) mechanism developed by their solution.

In the research that Wang et al. [21] conducted, they developed and evaluated a deep learning architecture called 3D-ResNet. This design made use of CT scans to differentiate between NTM-LD and MTB-LD, which are both diseases that are caused by Mycobacterium TB. A new customized deep learning algorithm (ACL) was presented by Akbulut [22] as the foundation for a resilient mechanism. This algorithm was created by combining CNN with LSTM and attention models. The marker-controlled watershed (MCW) segmentation method was utilized by the researchers in order to enhance the accuracy of classification in chest X-ray (CXR) pictures. This was accomplished by identifying important traces and stains.

Chouhan et al. [23] proposed a new DL architecture for the diagnosis of pneumonia. This architecture involves the use of a TL model. The ensemble module that they developed, which incorporated the outcomes of the pretrained models, was able to detect pneumonia with a higher degree of precision than any of the individual models that were used on their own. SynDiff is a new method that was presented by Dalmaz et al. [24] with the intention of enhancing the effectiveness of medical image translation. This approach is underpinned by the adversarial diffusion modelling framework. Through a conditional diffusion method, SynDiff was able to capture direct linkages in image distributions. This was accomplished by mapping noise and source images onto target images.

The contextual sensitivity of vision transformers, the precision of convolutional functions, and the realism of adversarial learning were all exploited by Dalmaz et al. [25] in their proposal for a generative adversarial method to medical picture synthesis. Dalmaz et al. One of the outcomes was ResViT. One of the most significant bottlenecks in the ResViT generator was due to an ART block, which was responsible for combining transformer and residual convolution components. During the course of their research, Yurt and colleagues [26] investigated a system that compiles information from a number of different picture sources by employing a combination of one-to-one and many-to-one streams. Through the utilisation of a fusion block, they were able to merge the information on matching mapping from one-to-one streams with the shared mapping features from many-to-one streams. There is still a pressing need for robust studies that can identify the presence of lung tumours and accurately categorizing the types of lung tumours, even though these studies represent substantial breakthroughs in automated methods for lung tumour classification. It is imperative that additional research and development activities be launched to fill this essential void in the detection of lung cancer.

III. Developed Methodology

The purpose of this research paper is to offer a cutting-edge system for the diagnosis of lung cancer. This system makes use of cutting-edge image processing techniques and deep learning methods that are at the cutting edge of the field, employing convolutional neural networks: CNNs. The system that we have constructed, trained, and evaluated makes use of a dataset that is available to the general public and was obtained from Kaggle [4]. Imagery of the chest obtained using computed tomography (CT) is included in this dataset. Before being fed into CNNs for the purpose of extracting deep features, the CT images are first subjected to a variety of preprocessing processes. After that, the features that were extracted from the CNNs that were the most successful are concatenated in order to produce a feature vector that is complete. Following this, the fused feature vector is subjected to analysis by a variety of classifiers in order to precisely determine whether or not lung cancer is already present. This section provides a comprehensive analysis of the suggested technique, as well as an in-depth explanation of each stage of the pipeline, which is illustrated in Figure 1.

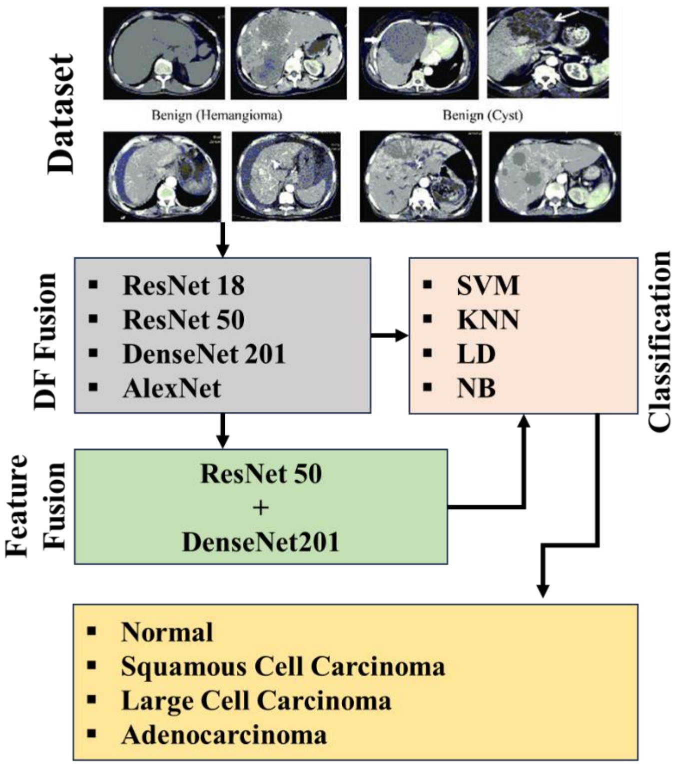

Figure 1. Developed Methodology Block Diagram

The cells that line the exterior of the lungs can undergo a transformation that is malignant, which can lead to the development of lung adenocarcinoma. This particular subtype is responsible for around forty percent of all instances of non-small cell lung cancer (NSCLC), as stated by the American Society of Clinical Oncology. The five-year survival rate for those who have stage 1 adenocarcinoma ranges from seventy percent to eighty-five percent. The prognosis, on the other hand, is significantly lower than thirty percent for patients who have locally advanced disease. Large cell carcinoma, on the other hand, is characterized by a rapid growth rate and a propensity to spread aggressively in comparison to other types of non-small cell lung cancer. It typically begins in the outer section of the lung. On the other hand, squamous cell carcinoma is a type of lung cancer that occurs more frequently in the central region of the lung or in significant airways such as the bronchi. Even while there is persistent conjecture regarding the potential connection between smoking behaviors and the prevalence of certain cancers, it is still difficult to gather information that can be considered conclusive with certainty. Large cell carcinomas and squamous cell carcinomas, on the other hand, can have disastrous repercussions and lead to high mortality rates if they are not treated by cancer specialists. Therefore, it is of the utmost importance for medical practitioners to swiftly commence suitable treatment strategies by precisely detecting and categorizing malignant tumours.

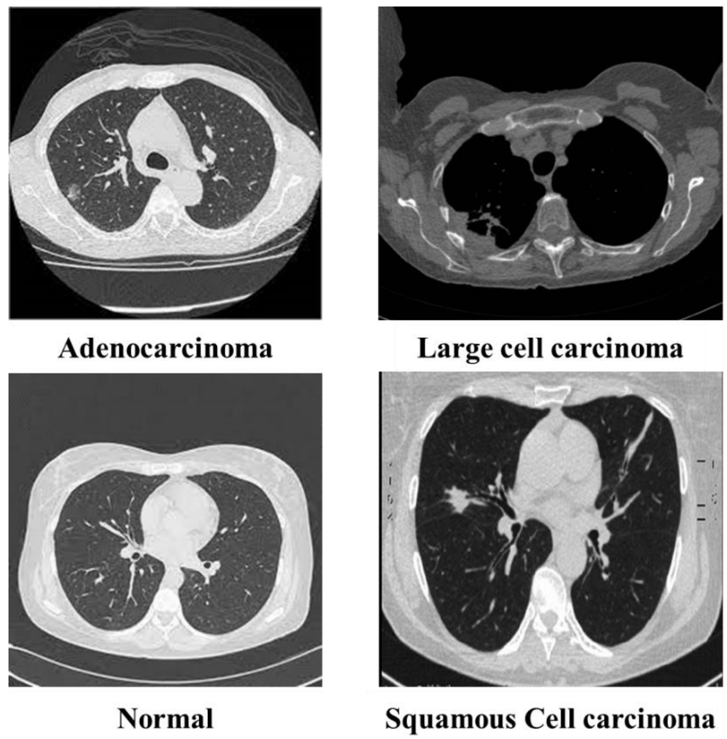

Figure 2. Dataset Computed tomography Images.

A. *Deep Feature Extraction*

During this part of the research, we focus on the approach used to extract features that are employed in the study. The investigation's framework relies heavily on the feature extraction process, which involves the use of four specific Convolutional Neural Network (CNN) architectures: ResNet18, ResNet50, DenseNet201, and AlexNet.

The choice of these CNN architectures is deliberate, as each possesses distinct qualities in terms of their structure and complexity. The intentional decision is made to utilize a wide range of characteristics, hence enhancing the ability to distinguish and classify within the generated set of features. Our goal is to combine features from different architectures to generate a composite feature space that has better discriminative properties and improved identification skills compared to separate feature sets. The incorporation of Residual Network (ResNet) design, as initially presented by the authors in [21], is of significant importance in this study. ResNet stands out for its ability to effectively train very deep CNN architectures, because to the inclusion of skip connections. These connections allow for the smooth integration of outputs from previous layers with those of stacked layers, which helps to avoid problems related to diminishing gradients and makes it easier to train deeper networks [22].

In addition, it is important to recognize the use of AlexNet, which was developed by Alex Krizhevsky and is particularly well-known for its impressive performance in the ImageNet Large Scale Visual Recognition Challenge. AlexNet's architecture consists of a well-chosen combination of convolutional and fully connected layers, resulting in an impressive top-5 error rate of 15.3%, which is 10.8% better than its competitors. The efficiency and extensive use of medical image identification highlights its significance in this research environment [23, 24].

In addition, the study utilizes the DenseNet201 architecture for the aim of extracting features. DenseNet is a CNN design that stands out for its remarkable depth of 201 levels. It introduces a new approach to CNN design by emphasizing dense connectivity patterns between layers. This strategy not only significantly decreases the number of parameters but also promotes strong feature transmission, alleviates the problem of vanishing gradients, and improves training simplicity. The fundamental concept behind DenseNet is that networks can reach higher levels of depth, accuracy, and ease of training by creating shorter connections between layers. This approach improves the flow of information and promotes the reuse of features [25]. To summarize, the careful selection and combination of several CNN architectures in the feature extraction procedure of this study are crucial in creating a thorough and distinguishing feature space. This methodology aims to enhance the effectiveness of subsequent analyses and identification tasks in the study area by utilizing the distinctive characteristics of ResNet, Alex Net, DenseNet201, and their respective contributions to deep learning architecture.

B. Fusion of Deep Convolutional Neural Network Features

Feature Fusion is the process of combining separate feature vectors into a single vector entity. During this part of the research, the deep features obtained from the highly skilled Convolutional Neural Networks (CNNs), namely DenseNet-201 and ResNet-50, were combined through fusion. The resulting vector demonstrates improved ability to distinguish and a wider range of applications when compared to the separate feature vectors. This improvement arises from the combination of characteristics derived from CNNs with varying depths and designs. Therefore, the new vector demonstrates significantly better performance compared to its individual components, indicating a significant improvement in feature representation and analysis within the research framework.

C. Classification

Subsequently, the novel feature vector is classified utilizing Error Correcting Output Code (ECOC) based classifiers, specifically Support Vector Machine (SVM), k-Nearest Neighbors (KNN), Naive Bayes (NB), and Linear Discriminant Analysis (LD). ECOC is an ensemble classification approach that combines many individual or binary classifiers to handle the complexities of multiclass classification scenarios. During this step, feature vectors are classified using ECOC-based SVM, KNN, LD, and NB classifiers.

The Support Vector Machine (SVM) is a well-known supervised learning technique used for classification problems. It is widely recognized and widely used due to its strong resilience and outstanding performance. SVM is a powerful technique for identifying complex data patterns by creating hyperplanes that maximize the separation between different classes. On the other hand, KNN functions by categorizing data points according to their closeness to the nearest neighbors, thus avoiding the need for explicit model training and instead depending on local knowledge for classification. The recognition of the incorporation of NB and LD classifiers is warranted. The former refers to a group of probabilistic classifiers that utilize Bayes' theorem and make naive assumptions about the independence of features. Although NB classifiers are simple, they can achieve impressive levels of accuracy, making them appropriate for a wide range of classification problems. On the other hand, Linear Discriminant Analysis (LD) is a statistical method that aims to distinguish between different classes by maximizing the distance between their respective centers, resulting in a linear representation of the data for classification purposes. The selection of these classifiers was based on their proven resilience and effectiveness in machine learning tasks, specifically in the field of medical picture classification. Their inclusion highlights a purposeful attempt to utilize known approaches that guarantee consistent performance and enable precise categorization of feature vectors obtained from the ECOC ensemble architecture.

IV. RESULTS

This section examines the results obtained from the recommended methodology. This study presents a novel approach to combining feature spaces extracted from the most efficient CNN architecture. The combined feature vectors are then classified using Error Correcting Output Code (ECOC) based classifiers.

A. Evaluation Metrics

The effectiveness of the proposed architecture is evaluated by using assessment criteria derived from the confusion matrix. The confusion matrix, known for its effectiveness, summarizes the performance of the framework in a compact tabular style. The proposed framework is evaluated using metrics derived from the confusion matrix, including accuracy, precision, and recall. These metrics can be calculated using Equations (1) through (3).

$$Precision = {TP}/{FP + TP}$$

$$Recall = {TP}/{FN + TP}$$

$$Accuracy = {TP + TN}/{FP + TP + FN + TN}$$

B. Performance of Proposed Method on Independent Feature Vectors

The highest possible scores for accuracy, precision, and recall were attained by the suggested method, which made use of separate feature vectors produced from ResNet18, ResNet50, AlexNet, and DenseNet201. These scores are presented in Table

1. Particularly noteworthy is the fact that ResNet50 and DenseNet201 achieved the greatest accuracy rates of 93.6% and 92.3%, respectively, when they were exposed to SVM classification. On the other hand, ResNet18 and AlexNet achieved top accuracy performances of 89.3 percent and 90.3 percent, respectively, which were achieved by KNN and LD classifiers.

Table 1. Independent Vector based result.

Feature Extractor	Recall	Precision	Accuracy
AlexNet	0.90	0.91	90.3%
DenseNet201	0.91	0.92	92.3%
ResNet50	0.94	0.93	93.6%
ResNet18	0.90	0.90	89.3%

The proposed model achieved remarkable success in achieving the best accuracy scores by utilising feature vectors taken from DenseNet-201 and ResNet-50. Afterwards, the feature vectors linked to the most successful designs, specifically ResNet-50 and DenseNet-201, were combined in a sequential way, resulting in a new fused feature vector. The succeeding section provides a detailed analysis and discusses the consequences of this combined feature vector.

C. Performance of Proposed Method on Fused Feature Vectors

During this stage, the two most successful feature vectors, specifically ResNet50 and DenseNet201, are combined in a sequential manner to produce a unique vector.

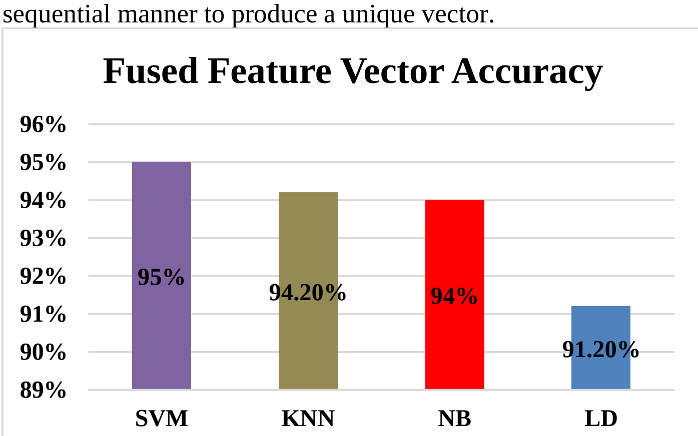

Figure 3. Fused Feature Vector based Accuracy.

The unique feature vector demonstrated exceptional performance by achieving an accuracy rate of 95% in SVM classification, surpassing the performance of the independent vectors. The assessment metrics, including accuracy, precision, and recall, obtained from the combined feature vectors are displayed in Figure 3, Figure 4, and Figure 5, correspondingly.

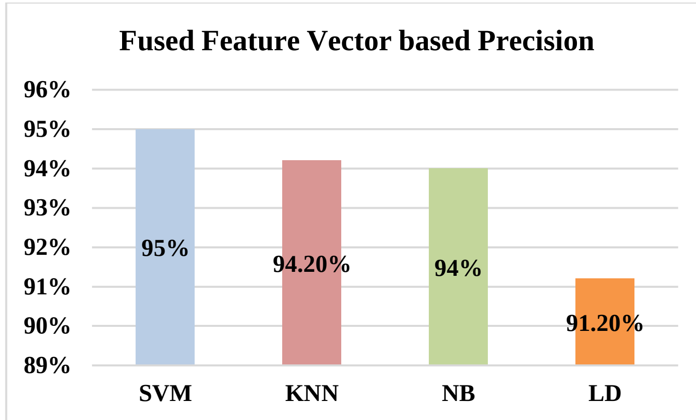

Figure 4. Fused Feature Vector based precision score.

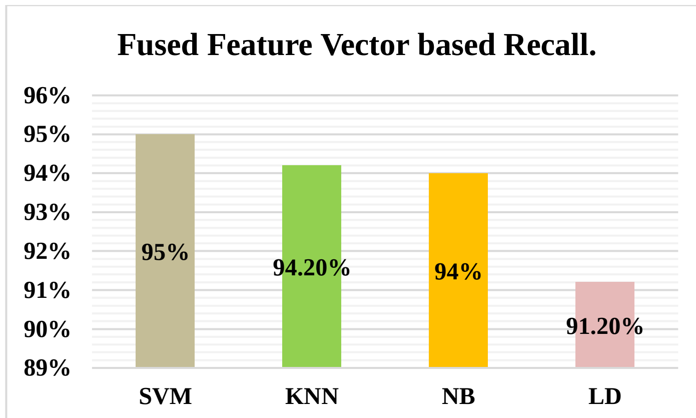

Figure 5. Fused Feature Vector based Recall Values.

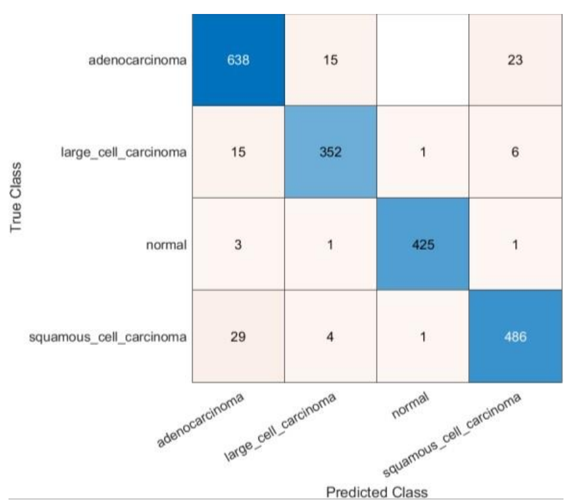

Figure 6. Support Vector Machine Confusion Matrix.

The confusion matrices obtained from the SVM and KNN classifiers are shown in Figure 6 and Figure 7, respectively. Furthermore, Figure 8 displays the confusion matrix generated by the Linear Discriminant (LD) classifier, whereas Figure 9 shows the confusion matrix produced by the Naive Bayes (NB) classifier. The feature vector under consideration achieved accuracy scores of 95%, 94.2%, 94%, and 91.2% when evaluated using SVM, KNN, NB, and LD classifiers, respectively.

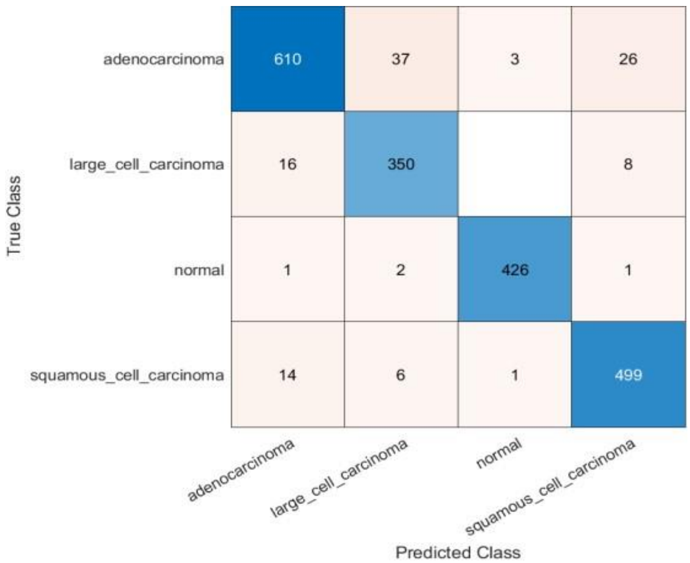

Figure 7. KNNs Confusion Matrix.

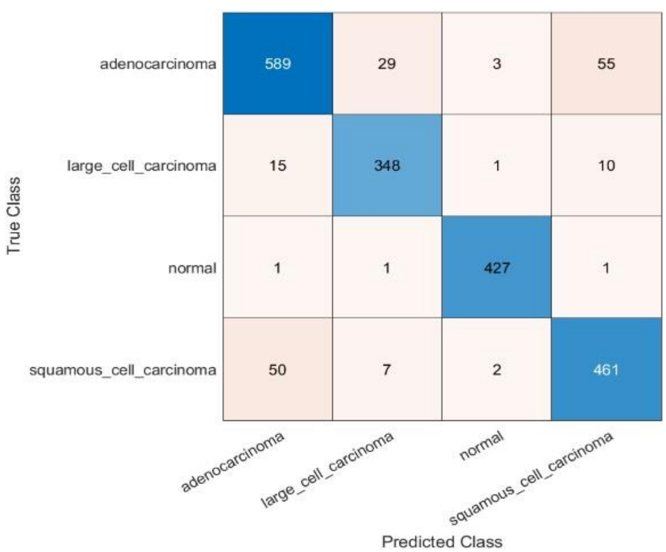

Figure 8. Linear Discriminant Confusion Matrix.

The results obtained from the proposed study highlight the strength and effectiveness of the new feature vector when compared to its individual components. The novel feature vector's superior performance compared to individual vectors can be due to its improved ability to distinguish and its extensive range of features. These properties arise from incorporating features retrieved from CNN architectures with varying complexities and depths. Therefore, the novel feature vector has exceptional performance, indicating its potential as a powerful tool for pattern recognition and classification tasks in the study field.

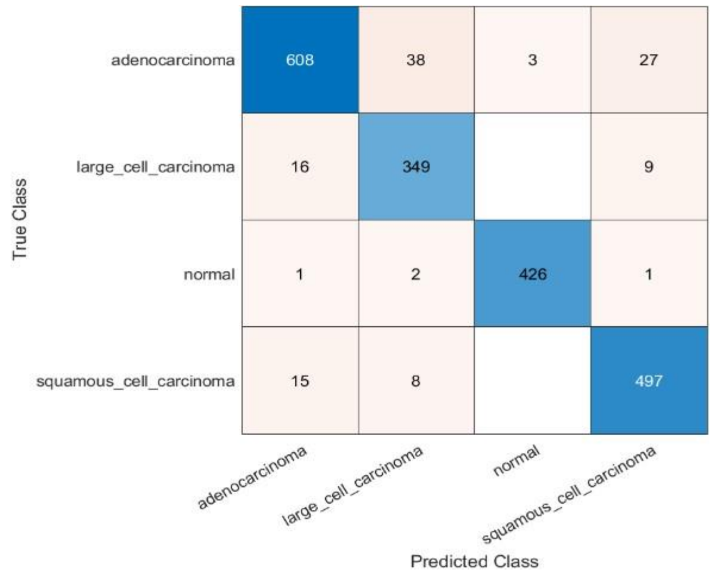

Figure 9. Naïve Bayes Confusion Matrix.

D. Comparison with Existing Techniques

This section provides a detailed comparison of the performance of our suggested strategy with the most advanced methods currently used in the field. The accuracy rate of our suggested method reached 95%, which is the greatest achieved so far, thanks to the innovative fused feature vector. On the other hand, Singh et al. [12] and Bhatia et al. [13] achieved accuracy rates of 88% and 84%, respectively, when classifying lung tumours. The outcomes derived from our suggested approach highlight its resilience and effectiveness in identifying and categorizing lung tumours from CT images. Hence, the framework has great promise for use in medical environments, allowing for the early and more accurate classification of lung tumours compared to current methods.

Table 2. Developed Methodology Comparison with existing Literature.

Reference	Model Utilized	Accuracy
Developed Methodology	**DenseNet201+ ResNet50**	**95%**
[12]	Multi-Layer Perceptron	88%
[13]	Unet	84%

E. Experimental Configuration

The lung tumour classification module is trained and assessed on an Intel Core i7 processor with 8 GB of RAM, using MATLAB 2021a. The dataset undergoes validation using a 10-fold cross-validation procedure. Cross-validation is a resampling technique used to evaluate machine learning models on a small data sample. Cross-validation, which is widely used in applied machine learning, is a method used to determine the effectiveness of a model on data that it has not been trained on. More precisely, it allows for the estimation of how well a model will perform using data that was not used to train the model. This provides valuable information about how well the model can be applied to new, unseen data. This strategy is preferred because of its simplicity and its ability to produce a more impartial or realistic assessment of model performance compared to other methods like a basic train/test split [26].

V. CONCLUSION & FUTURE WORK

Lung cancer is a highly challenging form of cancer that continues to be a major cause of cancer-related deaths globally. Identifying lung cancer at an early stage is crucial for improving patient survival rates. Usually, the diagnosis process includes the use of CT scans to precisely identify the locations of tumours and evaluate their level of malignancy. Modern computer-aided diagnosis (CAD) systems utilize artificial intelligence (AI) to automatically identify and categorize tumours from CT scans, enabling prompt intervention. These advanced systems utilize medical image processing, analysis, and computation to accurately detect tumour lesions. Deep learning, specifically, provides significant benefits compared to traditional machine learning methods. It allows for quick performance improvement and automatic extraction of important information from datasets, making the feature extraction process much simpler.

In this paper, we present an automated method for classifying lung tumours using advanced DL techniques. The framework we have developed has been extensively trained and evaluated using a publicly available dataset that consists of CT scans. At first, deep CNN features are extracted using ResNet18, ResNet50, AlexNet, and DenseNet201 architectures in a manner that reflects the expertise of a professional researcher. Afterwards, the feature vectors are classified using various classifiers such as SVM, KNN, LD, and NB. The top-performing feature vectors are combined to create a single vector that is more discerning and informative. The accuracy of our proposed vector is an impressive 95% when utilizing the fused feature vector, showcasing the effectiveness and high performance of our strategy. Moreover, our methodology shows potential for practical use in categorizing lung tumours based on medical images.

For future endeavours, our goal is to enhance our framework by integrating a wide range of databases that include MRI scans in addition to CT scans. In addition, we will conduct training and performance evaluations on various CNN architectures, including VGG-Net, ShuffleNet, and GoogLeNet. This will expand the range and practicality of our methodology in medical imaging tasks.

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AUTHORS

Abdulmohsen Algarni– Abdulmohsen Algarni received the PhD degree from Queensland University of Technology, Australia, in 2012. He was a research associate in the School of Electrical Engineering and Computer Science, Queensland University of Technology, Australia, in 2012. He is currently an associate professor at the College of Computer Science, King Khalid University. His research interests include Artificial intelligence, data mining, text mining, Machine Learning, information retrieval, and information filtering.

Ali Hamza – Ali Hamza pursue his bachelor degree from Department of Mechatronics Engineering, University of Engineering & Technology Peshawar, Pakistan.

Muhammad Anas – Department of Electrical & Electronics Engineering, Swinburne university of Technology Hawthorn Campus.

Muhammad Assam – Muhammad Assam working as Lecturer in Department of Software Engineering, University of Science and Technology Bannu KP Pakistan. His Research Interests include Brain Computer Interface, Computer Vision, Artificial Intelligence, Natural Language Processing and Medical Image Processing.

Correspondence Author – Abdulmohsin Algarni.