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Project on

Lung Cancer Detection on CNN combine model

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Abstract……………………………………………………………1

Chapter 1 Introduction………………………………………………...2

1.1 Research Background and Significance

1,2 Literature Review

1.3 Contribution of the Thesis

1.4 Summary

Chapter 2 Overview of Deep Learning Methods……………………13

2.1 Introduction

2.2 Overview of CNN

2.3 Le-Net

2.4 LSTM

2.5 Le-Net and LSTM

2.6 Summary

Chapter 3 Current Research…………………………………………21

Chapter 4 System Design and Development…………………………22

4.1 Preprocessing

4.2 Normalization

4.3 Proposed model

4.4 Model Evaluation

4.5 Confusion Matrix

4.6 Classification report

4.7 Summary

Chapter 5 Comparison with other models…………………………...33

Chapter 6 Results and Discussion ………..…..……………………...........38

Chapter 7 Conclusion and future work…..………………….............40

References……………………………………………………………..42

Abstract:

Lung cancer is an abnormality where the body's cells multiply uncontrollably. The disease can be deadly if not detected in the initial stage. To address this issue, an automated lung cancer malignancy detection using Le-Net combined with LSTM(Long Short Term Memory).Le-Net is a one type of CNN architecture. The Iraq-Oncology Teaching Hospital/National Center for Cancer Diseases (IQ-OTH/NCCD) lung cancer dataset was collected in the above-mentioned specialist hospitals over a period of three months in fall 2019. The image size is 512*512. It has total 1097 images. It has 3 classifications (Benign, Normal, and Malignant) images. The batch size and the channels are 32 and 3 respectively.

LSTM is a type of recurrent neural network (RNN) architecture designed to handle sequential data. It overcomes the vanishing gradient problem that traditional RNNs face by using a more complex memory cell. The proposed system utilized a convolution-based pre-trained LeNet model. LeNet was groundbreaking in introducing the concept of convolutional layers and max-pooling layers, which are now fundamental components of modern deep learning architectures. It consists of several convolutional layers followed by fully connected layers and uses activation functions. To evaluate the proposed model, a comparison is performed with other pre-trained models as feature extractors and also with the existing state-of-the-art methodologies as classifiers. The accuracy, sensitivity, and F1-Score of the proposed framework are 98.18%, 96.00%, and 98.17%, respectively. From the experimental results, it is evident that the proposed framework outperformed other existing methodologies. This work would be beneficial to both the practitioners and the patients in identifying whether the tumor is benign, malignant, or normal.

Chapter 1:

Introduction

1.1 research background and significance:

Lung cancer detection research is crucial due to the high mortality rate associated with this type of cancer. Early detection plays a vital role in improving patient outcomes, as the disease is often asymptomatic in its initial stages. The background of lung cancer detection research typically involves a deep dive into the risk factors associated with the disease, such as smoking, exposure to environmental pollutants, and genetic predisposition. Understanding these factors helps researchers identify high-risk populations and develop targeted screening strategies. The significance of this research lies in the potential to implement effective and non-invasive methods for early detection. Early diagnosis allows for timely intervention and increases the chances of successful treatment. Additionally, advancements in detection technology can contribute to personalized medicine, tailoring treatment plans based on individual patient profiles. The ongoing evolution of imaging techniques, such as CT scans and molecular imaging, along with the integration of artificial intelligence, has opened new avenues for improving the accuracy and efficiency of lung cancer detection. These advancements not only enhance diagnostic capabilities but also hold promise for reducing unnecessary invasive procedures and minimizing the economic burden associated with late-stage cancer treatments. In summary, lung cancer detection research aims to enhance our understanding of risk factors, develop effective screening methods, and leverage technological innovations to detect the disease in its early stages, ultimately improving patient outcomes and reducing the global burden of lung cancer.

1.2 Literature Review:

1. Artificial neural networks with the noble pursuit of saving lives, by providing a highly accurate, non-invasive method for early detection of lung cancer. In 2011, The authors in [1] combined artificial neural networks and fuzzy clustering methods. Their method was applied to a dataset of about 1000 images and obtained an accuracy of about 97%. The traditional artificial neural networks may not generalize well to unseen data, so the model's performance might degrade when applied to a different dataset, hospital, or geographical region.

2. In 2013 Another study proposed a CAD(computer-aided design) system where the authors claim to estimate survival rate in addition to the detection and prediction of lung cancer. They extracted features from a dataset containing 909 images and got an accuracy of about 96%.

3. In 2014, The researchers in [2] developed a computer-aided system based on artificial neural networks, their accuracy was around 90.63%. Utilizing a state-of-the-art Computer-Aided Diagnosis (CAD) system based on Artificial Neural Networks (ANN), an innovative approach for early lung cancer detection, significantly improving accuracy and reducing false positives. But this is an old model which is used in the early days in this field.

4. In 2016, The authors built a model on the PSO(particle swarm optimization) technique for lung cancer detection that included an SVM classifier and GLCM feature extraction. They yielded an accuracy of 89.6 percent in their work. In SVM, choosing the appropriate kernel function is tricky.

5. In 2018, The authors used a 3D CNN-based classification framework for lung nodules detection and classification. The pre-processing module, the 3D CNN module, and the classification module make up the proposed framework. The findings revealed that the suggested framework has a 95.5% detection accuracy and a 91.6% classification accuracy for benign and malignant nodules.

6. In 2019 Venkata Tulasiramu Ponnada, S.V. Naga proposed a model by Efficient CNN(EFFI-CNN) technology for Lung cancer detection. Experimental results show that the trained model has gained an overall accuracy of 87.00% on the validation data.

7. In 2020 Asuntha et al. developed a malignant lung nodule identification system using a unique Deep learning algorithm. The FPSO algorithm is used to find the best feature and classify it using the Deep Learning method in this study. An accuracy of 94.97% is achieved for the Real-Time data set in this work.

8. Researchers introduce a novel and enhanced deep neural network. In 2020, The authors use improved deep neural network (IDNN) technology for lung image(CT Image) segmentation and for feature selection which is done with the help of a hybrid intelligent spiral optimization-based generalized rough set approach. They also use an ensemble classifier for lung image classification. They got the overall accuracy is 96% but we all know that in deep neural networks, the issue of false positives in lung cancer detection remains a significant challenge.

9. In 2020 Shanid et al. [23] suggested a deep learning and hybrid optimization algorithm-based lung cancer screening technique. The nodules are segmented and identified using a grid-based technique and classified using a deep learning network-based slap elephant herding optimization algorithm. This work achieves a 96% accuracy rate.

10. In 2020 a Computer-aided system was introduced for detecting lung cancer in a dataset collected from Iraqi hospitals by using a convolutional neural network technique with AlexNet architecture for helping with the diagnosis of the patient's cases: normal, benign, or malignant. The proposed model gives a high accuracy up to 93.548%.

11. In 2020, Kalaivani et al. classified CT scans of the lungs as either normal or malignant using an adaptive boosting algorithm that was implemented using DenseNet Architecture which is one of the popular CNN architecture that was trained on Clinical Data. Experimental results showed that this method achieved an accuracy of 90.85%.

12. In 2021 Shan et al. devised a lung cancer detection system based on the ITEO algorithm. In this method for lung area segmentation, Kapur entropy maximization and ITEO-based feature selection methods are used. The accuracy of 92.27% is obtained by this work.

13. In 2021, Heuvelmans, M.A., presented a Lung cancer prediction by Deep Learning to recognize benign lung nodules. The input images were fed to pre-processing to eliminate noise. Lung Cancer Prediction was done with the help of Convolutional Neural Network. It provides a high F-Score with low accuracy

14. In 2021 a model by transfer learning of a pre-trained deep neural network, the GoogLeNet was employed to develop a learning model of the IQ-OTH/NCCD lung cancer dataset. GoogLeNet is a type of convolutional neural network based on the Inception architecture Experimental results show that the trained model has gained an overall accuracy of 94.38% on the validation data.

15. Gao et al. utilized pre-trained VGG16 on the LUNA16 dataset to identify lung nodules in 2021. They initially investigated three cutting-edge convolutional neural network (CNN) models, namely VGG16, VGG19, and ResNet50. They concluded that VGG16 was the best model for lung nodule identification, with an accuracy of 96.86%.

16. In 2022, The authors use 3D CNN to detect lung cancer which provides better results in comparison to the 2D CNN. This research describes a method for classifying lung cancers as malignant or benign that employs a 3D convolutional neural network (3D CNN). They use it in a very simple way and it can undertake feature engineering on its own but by using combined or hybrid deep learning models get more accurate and better performance.

17. One of the combined models we can say, In 2022 The authors use the CNN+IMFO+LBP combined method and they get better performance compared to the traditional methods(SVM, KNN, MFO, WTEEB). This suggested model for accuracy is 7.35%, 2.99%, 0.73%, 1.84%, and 4.05% better than SVM, KNN, CNN, MFO, WTEEB, and GWO+FRVM models. However, the problem is that the computation time of this model is not much better.

18. IN 2022 A dynamic model is proposed to detect lung cancer where the Cuckoo search optimization (CSO) has integrated with neural network and efficient feature extraction method LBP (Linear Binary Pattern)(CSO+LBP) to apply on lung cancer datasets for nodule selection. This dynamic model is better than particle swarm optimization(PSO) with Linear Binary Pattern(LBP)(PSO+LBP). The integration of these techniques makes it challenging to replicate the results.

19. In 2023 a novel deep learning framework formulated by the encapsulation of a Convolutional Neural Network (CNN) and a Capsule Neural Network (CapsNet) called LCD-CapsNet, leveraging the capabilities of these networks to minimize vast amounts of data and achieve spatial invariance for lung cancer detection and classification using CT images. The results demonstrated that LCD-CapsNet outperforms CapsNet, with an Accuracy of 94 % of benign and malignant data.

20. In 2023, the authors suggested a deep learning-based LeNet model for assessing and classifying lung cancer on a limited dataset. The accuracy of this model is 97.88%, the sensitivity is 93.14%, and the specificity is 95.91%. On big datasets, the outcome may be enhanced by utilizing additional deep detectors, additional feature extractors, sophisticated hyper-parameter optimizations, a hybrid model, and detection performance evaluation.

1.3 Contribution of the Thesis:

Our model is not a simple cnn model. The model is cnn Hybrid model. The name of the Hybrid model is Le-net and LSTM.

LeNet is a convolutional neural network (CNN) architecture, designed for handwritten and machine-printed character recognition. It was introduced by Yann LeCun and his colleagues in the 1990s. LeNet played a pioneering role in the development of CNNs and is particularly known for its application in early optical character recognition systems. The architecture consists of multiple convolutional and pooling layers, followed by fully connected layers. LeNet's hierarchical structure allows it to effectively capture and learn hierarchical features in input images.

LSTM is a type of recurrent neural network (RNN) architecture designed to address the vanishing gradient problem in traditional RNNs. LSTMs are widely used in natural language processing (NLP) and sequential data tasks due to their ability to capture long-term dependencies. Unlike standard RNNs, LSTM units have a more complex structure, including memory cells and gating mechanisms. This enables LSTMs to retain information over longer sequences, making them well-suited for tasks such as language modeling, speech recognition, and sequence prediction. In summary, LeNet is a CNN architecture primarily used for image recognition tasks, while LSTM is an RNN architecture designed to handle sequential data and is commonly applied in tasks involving natural language processing and time-series analysis.

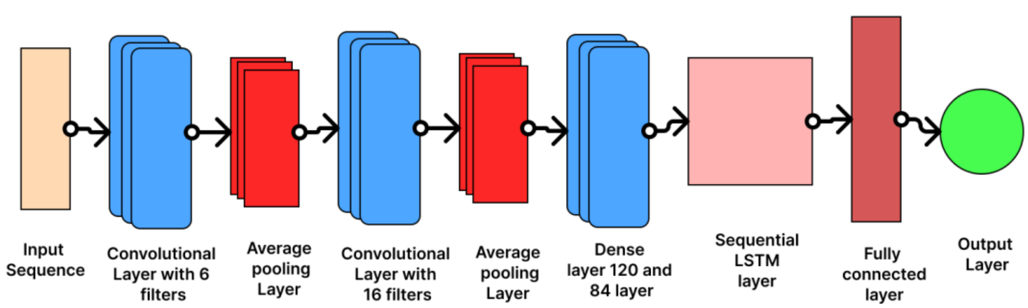


Fig: Block diagram of Le-net and LSTM

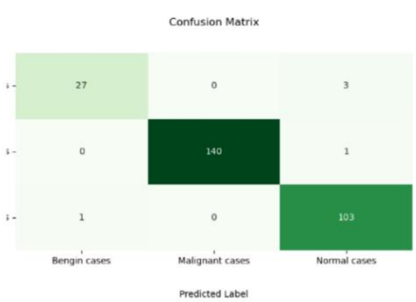
The combined model integrates the LeNet-5 and LSTM components to work in tandem for the image classification task. The LeNet-5 model is placed at the beginning to extract image features. The LSTM model follows, processing the feature vectors extracted by LeNet-5 in a sequential manner. Output Layer: A final Dense layer with the number of classes (n_classes) and a softmax activation function provides the model's output, which represents the predicted class probabilities. The combined model aims to leverage the strengths of both the LeNet-5 CNN for feature extraction and the LSTM for capturing sequential information

The greatest performance is this model's primary contribution. As a result of the combination model's small output parameter.

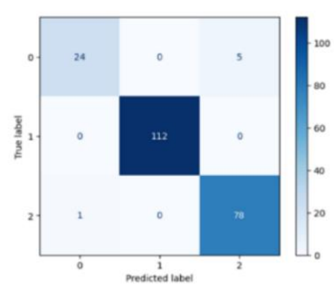
The test accuracy is 98.18% and the Specificity is 98.20% where. The simple Le net model paper’s parameter accuracy is 97.88 and Specificity 95.91% [22]

The time complexity is less than other hybrid model and the epochs is only 10 . Our model can perform a small data and also a large dataset and the model architecture is less complex and less difficulty and very simplicity. This model can also use the augmentation images of lung cancer.

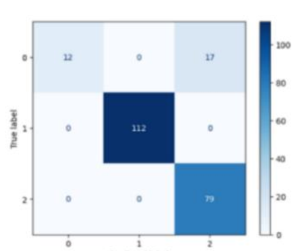
The perform matrix of Le-net and LSTM combine model can compare with other model:



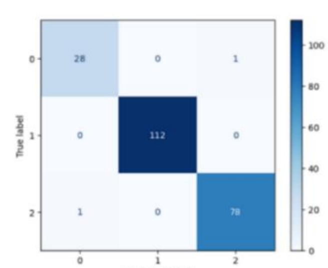
Le Net-5 + LSTM



(c) MobileNetV2+MLP



(d) VGG16+KNN



(a) VGG16+MLP

Here our proposed model performance is very good compared with other papers. This compares photo collection with this reference [23].

Here, There are two graphs which are Accuracy, Value accuracy and Epochs The other graphs are Loss, value loss, and epochs.

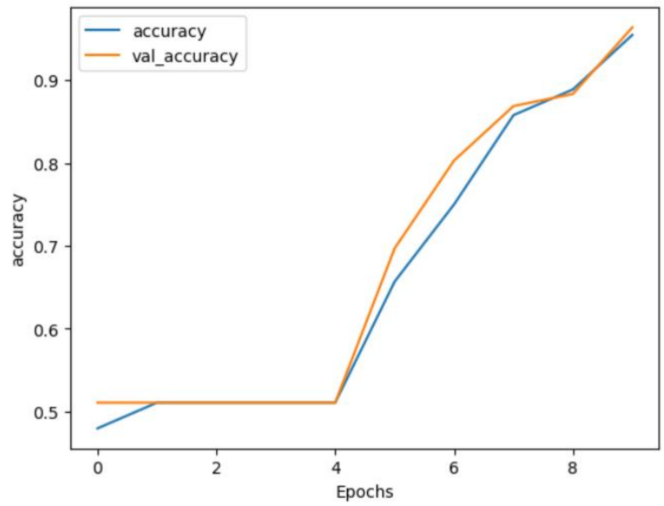


Fig: Accuracy , value accuracy and Epochs

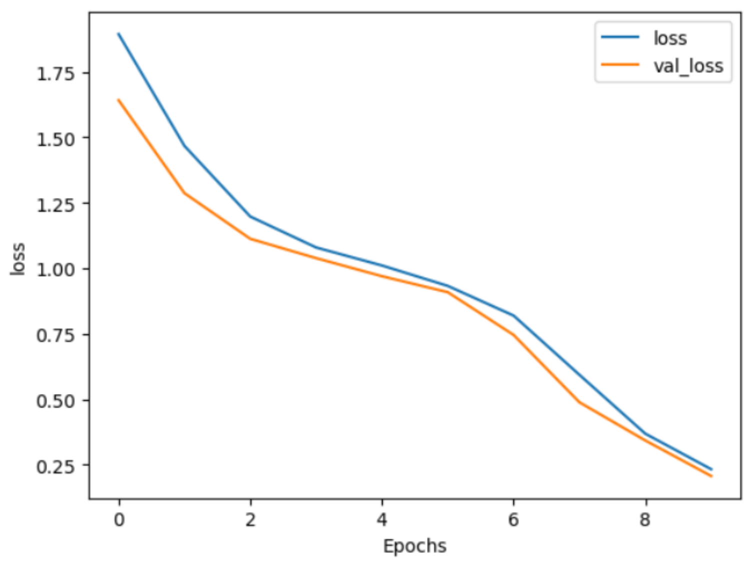


Fig: Loss , value loss and Epochs

1.4 Summary:

Cancer is defined as the fast formation of aberrant cells that expand beyond their normal borders and can later infiltrate neighboring sections of the body and spread to other organs; this latter phase is known as metastasis. The leading cause of cancer mortality is widespread metastasis. Cancer is the largest cause of mortality in the globe, accounting for over 10 million deaths in 2020, or roughly one in every six.

In 2020, the following were the leading causes of cancer death: lung (1.80 million deaths); lung (2.21 million cases). Early detection and treatment of cancer reduces mortality. Early detection has two components: early diagnosis and screening. When cancer is detected early, it is more likely to react to therapy, resulting in a higher likelihood of survival with less morbidity and less expensive treatment. Lung cancer is the world's second most frequent cancer. It is the most prevalent type of cancer in males and the second most frequent type of cancer in women. Diagnosis of Lung Cancer Based on CT Scans Using CNN] According to the statistics of the American Cancer Society, lung cancer is the primary cancer killer in the United States . The overall estimated number of new cases of all types of cancer in 2020 was 1660290 (854790 for men and 805500 for women), of which the number of lung cancer accounted for 13.7% of the incidences. Whereas the total number of estimated death cases of cancer were 580350 cases (306920 for men and 273430 for women), 27.5% of these were for cases diagnosed with lung cancer with close shares for both genders.

[Siegel, Rebecca, Naishadham, Deepa, Jemal, and Ahmedin., "Cancer statistics, 2020," A Cancer Journal For Clinicians, vol. 63, no. 1, pp. 11-30, 2013..]

According to the latest WHO data published in 2020 Lung Cancers Deaths in Bangladesh reached 12,174 or 1.70% of total deaths. The age-adjusted Death Rate is 10.24 per 100,000 of population ranks Bangladesh 102 in the world.

Lung tumors may not have specific symptoms initially and are broadly divided into benign (non-cancerous) and malignant (cancerous). When a patient is diagnosed with a lung tumor, the next step is to identify whether the tumor is benign or malignant. Benign tumors are non-cancerous masses that grow slowly. The cells within the benign tumor always lie within the tumor boundary and will not spread or invade nearby tissues. Sometimes benign tumors can evolve into enormous masses of tissues with well-defined boundaries and are not harmful. However, malignant tumors are cancerous tumors that can spread to any body part through the circulatory system or the lymph. These tumors invade nearby cells easily and will not have well-defined boundaries. Owing to the rapid proliferation, these malignant tumors may eventually return even after surgery. There are various imaging modalities for lung cancer detection. Computed Tomography (CT), PET (Positron Emission Tomography), and MRI (Magnetic Resonance Imaging) are widely used for lung abnormality detection. Here we take the CT images for lung cancer detection and classification.

The dataset was organized into a structured image dataset format suitable for deep learning tasks. All images in the dataset were resized to a consistent dimension of 512x512 pixels. This step ensures uniformity and compatibility in terms of input image size for our deep learning models. The dataset was shuffled to eliminate any inherent ordering effects that might bias the model during training. This step ensures that the model learns from a well-mixed set of examples. Images were grouped into batches to facilitate efficient model training. A batch size of 32 was selected for this study, which balances computational efficiency and model convergence. The class labels associated with each image were encoded to numerical values, allowing the model to perform multiclass classification. The class names were retrieved and can be mapped back to their respective labels. A random seed of 42 was used to ensure reproducibility in the shuffling and dataset-splitting processes. These preprocessing steps are crucial in preparing the dataset for the subsequent stages of model training and evaluation. The resized, shuffled, and batched dataset is use in training and validating deep learning models for lung cancer detection and classification.

The model is meticulously constructed to harness the power of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, culminating in an innovative fusion of visual and sequential data analysis. At the core of this pioneering model is a fusion of two potent neural network architectures: the iconic LeNet-5, renowned for its proficiency in visual pattern recognition, and LSTM with self-attention mechanisms to decode the temporal sequences within the data. This hybrid architectural framework integrates the strengths of both CNNs and recurrent neural networks, aiming to comprehensively capture intricate patterns and dependencies that exist in medical imaging data.

As part of disease classification, various pre-processing techniques can be applied to medical imaging. Studies reveal that pre-processing enhances the efficiency of the model. Researchers proposed various methodologies for lung cancer diagnosis using machine learning techniques. In the case of machine learning, relevant features must be manually extracted with the help of domain expertise, but sometimes inaccurate feature selection may impact the classifier. Chaganti et al. [21] suggested that in image classification, Traditional machine learning approach is superseded by deep learning because of its computational efficiency. Deep learning enables the extraction of fundamental and complicated features automatically rather than manual feature extraction. Our proposed method employs lung CT imaging modality for malignancy detection. In our proposed model, we choose Le-Net and LSTM combined model. We have utilized pre-trained Le-Net as a feature extraction. The model could improve performance when compared to other deep learning techniques.

Chapter 2:

Overview of Deep Learning Methods

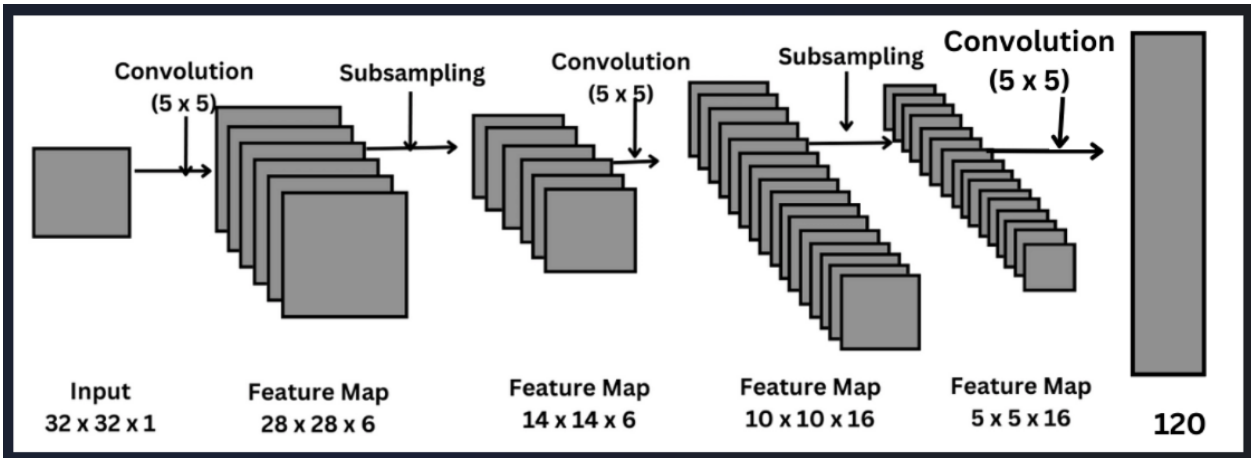
2.1 Introduction:

Nowadays, deep learning (DL), a subfield of artificial intelligence (AI) and machine learning (ML), is seen as a key technology of the Fourth Industrial Revolution (4IR, or Industry 4.0). Artificial neural networks (ANNs) are the source of deep learning (DL) technology, which has gained popularity in the computer community due to its ability to learn from data. It is used extensively in a broad range of application domains, including cyber security, healthcare, text analytics, and visual identification. However, building an appropriate DL model is a challenging task, due to the dynamic nature and variations in real-world problems and data. Moreover, the lack of core understanding turns DL methods into black-box machines that hamper development at the standard level. This article presents a structured and comprehensive view on DL techniques including a taxonomy considering various types of real-world tasks like supervised or unsupervised. In our taxonomy, we take into account deep networks for supervised or discriminative learning, unsupervised or generative learning as well as hybrid learning and relevant others. We also summarize real-world application areas where deep learning techniques can be used. Finally, we point out ten potential aspects for future generation DL modeling with research directions. Overall, this article aims to draw a big picture on DL modeling that can be used as a reference guide for both academia and industry professionals.

2.2 Overview of CNN:

A convolutional neural network is a feed-forward neural network that is generally used to analyze visual images by processing data with grid-like topology. It's also known as a

ConvNet. A convolutional neural network is used to detect and classify objects in an image [25]. It contains a series of pixels arranged in a grid-like fashion that contains pixel values to denote how bright and what color each pixel should be. The convolution layer is the core building block of the CNN. It carries the main portion of the network's computational load



Convolutional layer. The majority of computations happen in the convolutional layer, which is the core building block of a CNN. A second convolutional layer can follow the initial convolutional layer. The process of convolution involves a kernel or filter inside this layer moving across the receptive fields of the image, checking if a feature is present in the image.

Over multiple iterations, the kernel sweeps over the entire image. After each iteration a dot product is calculated between the input pixels and the filter. The final output from the series of dots is known as a feature map or convolved feature. Ultimately, the image is converted into numerical values in this layer, which allows the CNN to interpret the image and extract relevant patterns from it.

Pooling layer. Like the convolutional layer, the pooling layer also sweeps a kernel or filter across the input image. But unlike the convolutional layer, the pooling layer reduces the number of parameters in the input and also results in some information loss. On the positive side, this layer reduces complexity and improves the efficiency of the CNN.

Flattening Layer: After several convolutional and pooling layers, there's a flatten layer. This layer transforms the 2D feature maps into a 1D vector, preparing the data for the fully connected layers that follow.

Fully connected layer. The FC layer is where image classification happens in the CNN based on the features extracted in the previous layers. Here, fully connected means that all the inputs or nodes from one layer are connected to every activation unit or node of the next layer.

All the layers in the CNN are not fully connected because it would result in an unnecessarily dense network. It also would increase losses and affect the output quality, and it would be computationally expensive.

There are several popular Convolutional Neural Network (CNN) architectures, each with its own unique design and characteristics. Some of the well-known CNN architectures include:

LeNet-5 , AlexNet , VGGNet, GoogLeNet, ResNet, DenseNet, MobileNet, EfficientNet, Xception SqueezeNet

2.3 Le-Net:

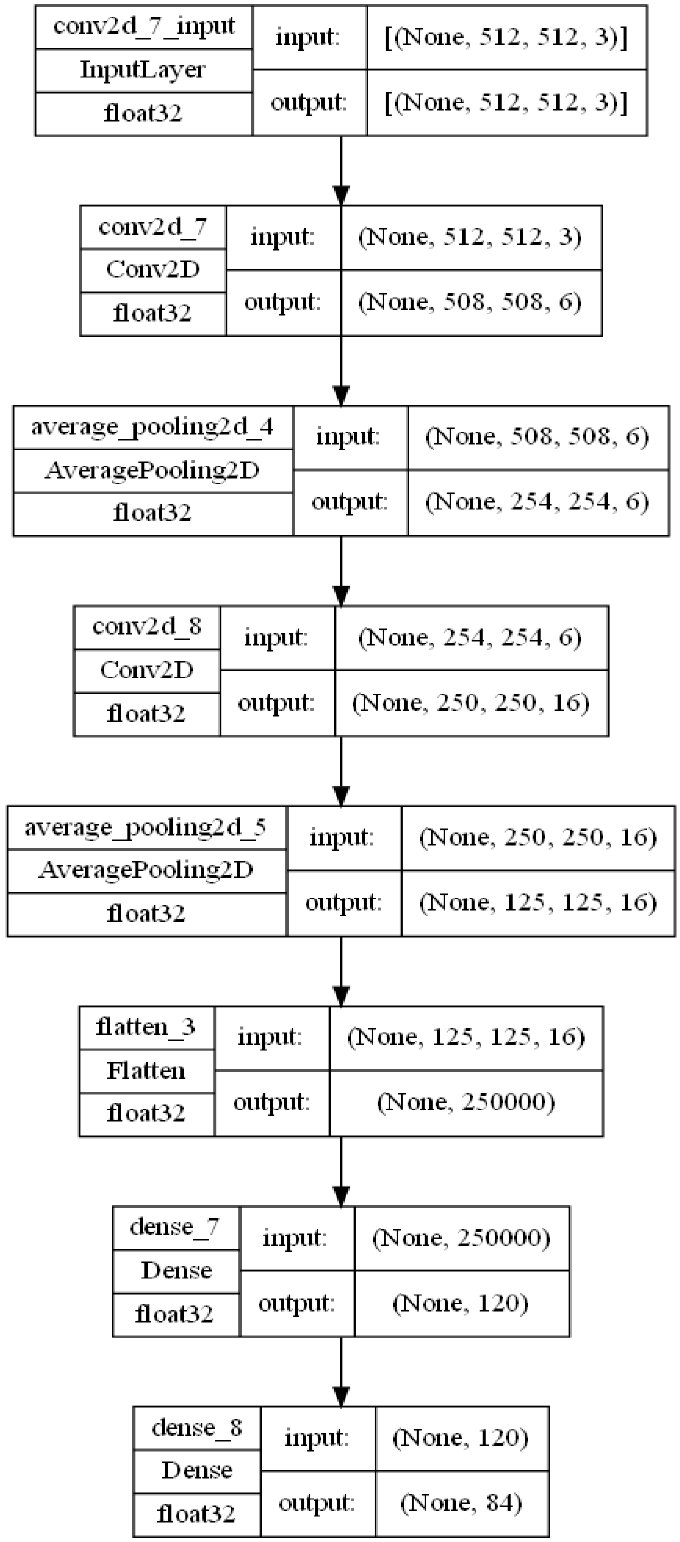


Fig: Le-Net model architecture

LeNet-5 is a convolutional neural network (CNN) architecture that was designed for handwritten and machine-printed character recognition. It was introduced by Yann LeCun and his colleagues in 1998. LeNet-5 consists of seven layers, including convolutional layers, subsampling layers, and fully connected layers.

LeNet is a popular DNN based model with a simple and effective architecture that also consumes very less implementation time. As like most of the DNN models, LeNet also uses MaxPooling layer for dimensionality reduction by eliminating the information of minimum valued elements.

The LeNet-5 model begins with an input layer designed for grayscale images with a resolution of 32x32 pixels. The first layer, a convolutional layer (C1), utilizes six 5x5 filters with the Rectified Linear Unit (ReLU) activation function, resulting in an output of 28x28x6 feature maps. This layer extracts low-level features from the input images.

Following C1, a pooling layer (S2) applies 2x2 average pooling, reducing the spatial dimensions to 14x14x6. This pooling operation helps the network become more invariant to small translations in the input.

The second convolutional layer (C3) employs 16 filters of size 5x5 with ReLU activation, producing feature maps of size 10x10x16. This layer captures more complex patterns and features in the input.

Another pooling layer (S4) with 2x2 average pooling follows C3, further decreasing the spatial dimensions to 5x5x16. This reduction aids in simplifying the representation while retaining important information.

The Flatten layer transforms the 3D output of the previous layer into a 1D vector with 400 elements, preparing the data for the fully connected layers.

The first fully connected layer (C5) consists of 120 units with ReLU activation, contributing to higher-level feature extraction. Subsequently, a second fully connected layer (F6) with 84 units refines the extracted features further.

The output layer, the final stage of the network, has units equal to the number of classes (e.g., 10 for digit recognition). It employs the softmax activation function to produce a probability distribution over the classes, representing the model's prediction for the input.

2.4. LSTM :

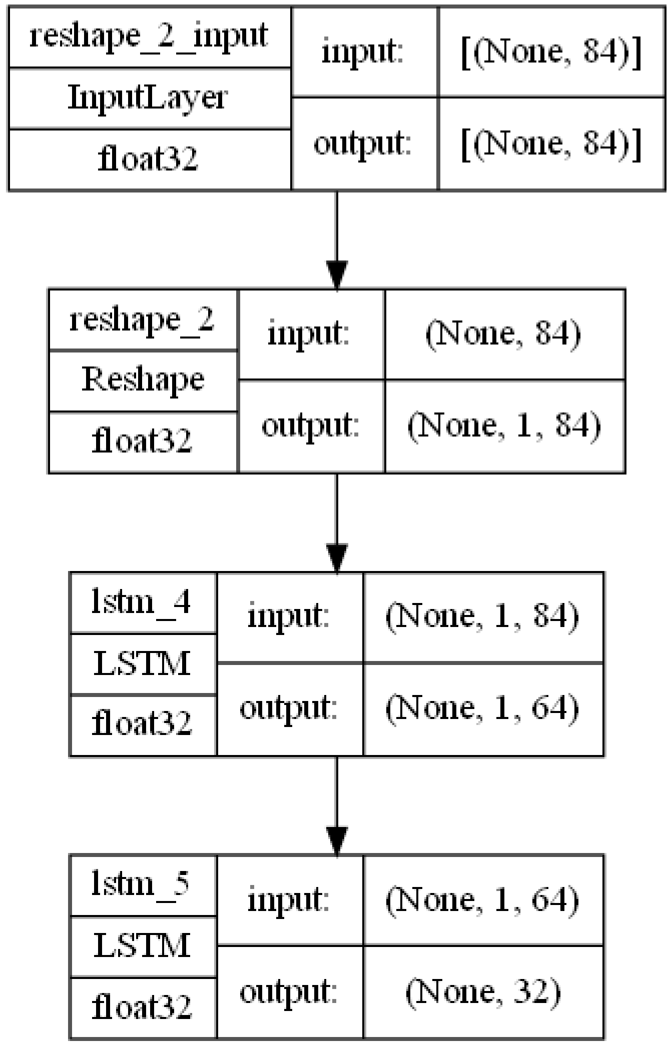


Fig: LSTM model architecture

Long Short-Term Memory Networks is a deep learning, sequential neural network that allows information to persist. It is a special type of Recurrent Neural Network which is capable of handling the vanishing gradient problem faced by RNN. LSTM was designed by Hochreiter and Schmidhuber that resolves the problem caused by traditional rnns and machine learning algorithms. LSTM can be implemented in Python using the Keras library.[26]

The input layer receives sequential data, such as time series or natural language sequences. Each input sequence is represented as a matrix with dimensions (time_steps, features)The first LSTM layer processes the input sequence.Each LSTM unit in this layer has memory cells capable of capturing long-term dependencies.After the LSTM layers, a Dense layer may be added for the final output.The Dense layer transforms the learned features into the desired output format.The LSTM model in the image is a three-layer model. The first layer is the input layer, which takes a vector of 84 features as input. The second layer is the LSTM layer, which has 64 hidden units. The third layer is the output layer, which has 32 hidden units.The first layer in the model is a reshape layer that reshapes the input tensor from (None, 84) to (None, 1, 84). This is necessary because LSTM layers expect their input to be three-dimensional, with the first dimension representing the batch size, the second dimension representing the timesteps, and the third dimension representing the features. In this case, the batch size is None (which means that it can be any size), the timesteps is 1 (which means that the input is a single sequence), and the features is 84 (which means that there are 84 features in the input sequence).

The second layer in the model is an LSTM layer with 64 units. This layer takes the reshaped input tensor and outputs a 2D tensor of shape (None, 1, 64). The 64 units in the LSTM layer represent the hidden state of the model, which is a vector of 64 numbers that summarize the information that the model has learned from the input sequence up to that point.

The third layer in the model is another LSTM layer with 32 units. This layer takes the output of the first LSTM layer and outputs a 2D tensor of shape (None, 32). The 32 units in this layer represent the final output of the model, which is a vector of 32 numbers that represents the model's prediction for the next element in the input sequence.

2.5 Le-net and LSTM:

The proposed model is a novel architecture that combines the classic LeNet-5 convolutional neural network (CNN) with a Long Short-Term Memory (LSTM) recurrent neural network (RNN).

This combined algorithm consists of four layers.

Reshape 2 input: This layer reshapes the input image to have three dimensions, (None, 1, 84). This is necessary because the LSTM layer expects its input to be three-dimensional.

LSTM 4: This is the LSTM layer. It has 64 hidden units and a return sequence length of 1. This means that the layer outputs a vector of 64 hidden units for each time step in the input sequence.

LSTM 5: This is another LSTM layer. It has 32 hidden units and a return sequence length of 1. This layer outputs a vector of 32 hidden units for each time step in the input sequence.

Dense 4: This is a dense layer with 9 hidden units. The layer outputs a vector of 9 hidden units, which represents the probability of the input image belonging to each of the nine classes.

The final activation function of the dense layer is softmax

The combined model integrates the LeNet-5 and LSTM components to work in tandem for the image classification task. The LeNet-5 model is placed at the beginning to extract image features. The LSTM model follows, processing the feature vectors extracted by LeNet-5 in a sequential manner. Output Layer: A final Dense layer with the number of classes (n_classes) and a softmax activation function provides the model's output, which represents the predicted class probabilities. The combined model aims to leverage the strengths of both the LeNet-5 CNN for feature extraction and the LSTM for capturing sequential information

The batch size of the model is fixed which is 32 and image size is same 512 *512 and channel size is 3. Finally build this model in this parameter. The model is optimized using the Adam optimizer, and loss is calculated using sparse categorical cross-entropy. And the matrix value is accuracy. Finally fit this model by using 10 epochs. In following this stapes the final accuracy of our proposed model is 98.18% and the loss is 19.65%

2.6 Summary:

LeNet:

LeNet, short for LeNet-5, is a convolutional neural network (CNN) architecture designed for handwritten and machine-printed character recognition. It was introduced by Yann LeCun and his colleagues in the 1990s. LeNet played a pioneering role in the development of CNNs and is particularly known for its application in early optical character recognition systems. The architecture consists of multiple convolutional and pooling layers, followed by fully connected layers. LeNet's hierarchical structure allows it to effectively capture and learn hierarchical features in input images.

LSTM (Long Short-Term Memory):

LSTM is a type of recurrent neural network (RNN) architecture designed to address the vanishing gradient problem in traditional RNNs. LSTMs are widely used in natural language processing (NLP) and sequential data tasks due to their ability to capture long-term dependencies. Unlike standard RNNs, LSTM units have a more complex structure, including memory cells and gating mechanisms. This enables LSTMs to retain information over longer sequences, making them well-suited for tasks such as language modeling, speech recognition, and sequence prediction. In summary, LeNet is a CNN architecture primarily used for image recognition tasks, while LSTM is an RNN architecture designed to handle sequential data and is commonly applied in tasks involving natural language processing and time-series analysis.

Chapter 3

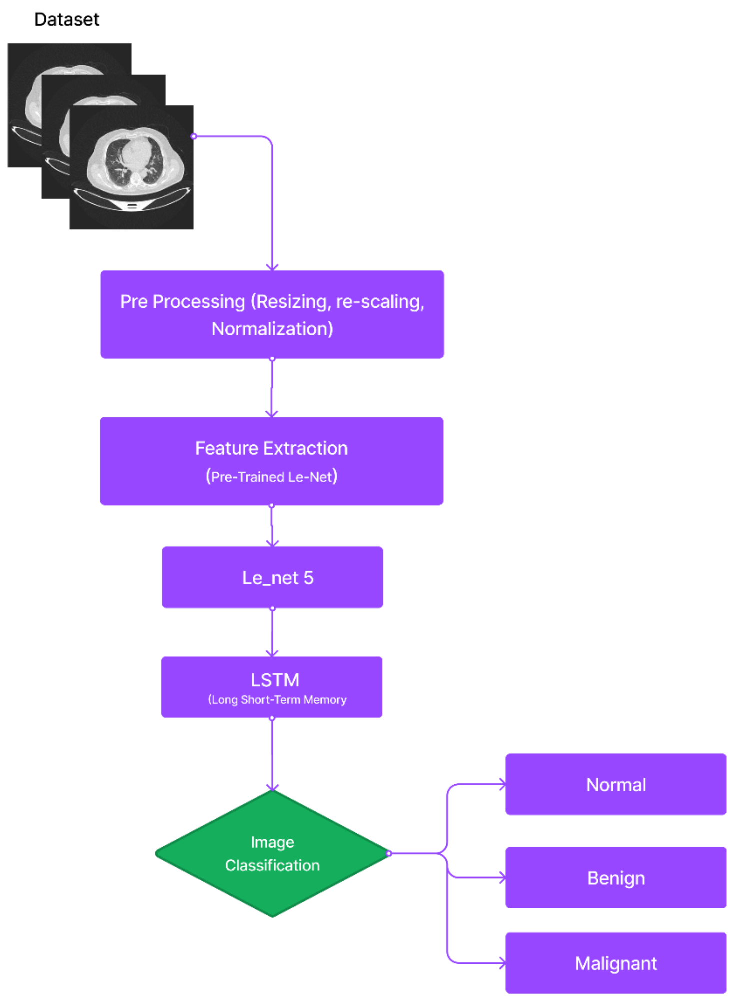
Current Research on Lung cancer classification

In 2020 a Computer-aided system was introduced for detecting lung cancer in a dataset collected from Iraqi hospitals by using a convolutional neural network technique with AlexNet architecture for helping with the diagnosis of the patient's cases: normal, benign, or malignant. The proposed model gives a high accuracy up to 93.548%. In 2020, Kalaivani et al. classified CT scans of the lungs as either normal or malignant using an adaptive boosting algorithm that was implemented using DenseNet.Experimental results showed that this method achieved an accuracy of 90.85%.In 2021 a model by transfer learning of a pre-trained deep neural network, the GoogLeNet was employed to develop a learning model of the IQ-OTH/NCCD lung cancer dataset.

GoogLeNet is a type of convolutional neural network based on the Inception architecture Experimental results show that the trained model has gained an overall accuracy of 94.38% on the validation data.Gao et al. utilized pre-trained VGG16 on the LUNA16 dataset to identify lung nodules in 2021. They concluded that VGG16 was the best model for lung nodule identification, with an accuracy of 96.86%.In 2023 a novel deep learning framework formulated by the encapsulation of a Convolutional Neural Network (CNN) and a Capsule Neural Network (CapsNet) called LCD-CapsNet,In 2023, the authors suggested a deep learning-based LeNet model for assessing and classifying lung cancer on a limited dataset. The accuracy of this model is 97.88%,

Chapter 4

System Design and Development



4.1. Pre-processing:

Preprocessing means converting the available row image data into a common attribute to properly process images. The data may be collected from a different platform or different places that's why all the image is not the same in size. These data can not directly pass to the neural network so there is a need so there is need to be converting all data attributes similarly[.4]

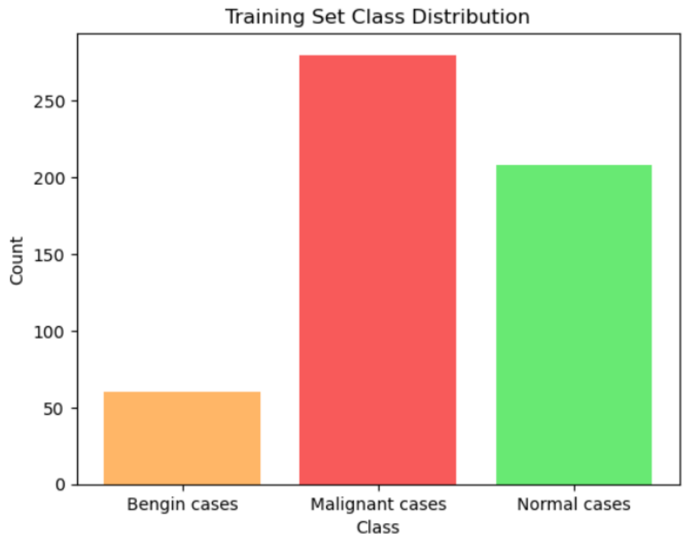
Resizing: First resizing the images to a standard size which is 512 * 512. The initial image which is resized to 512*512*3 dimension.Resizing allows you to make your image smaller or larger without cutting anything out. Resizing alters the image's dimensions, which typically affects the file size and image quality.

Batch Size: The batch size is 32 which determines how many images are processed at once during training. shuffle is randomizing the order of your training data to avoid the model learning sequential patterns.

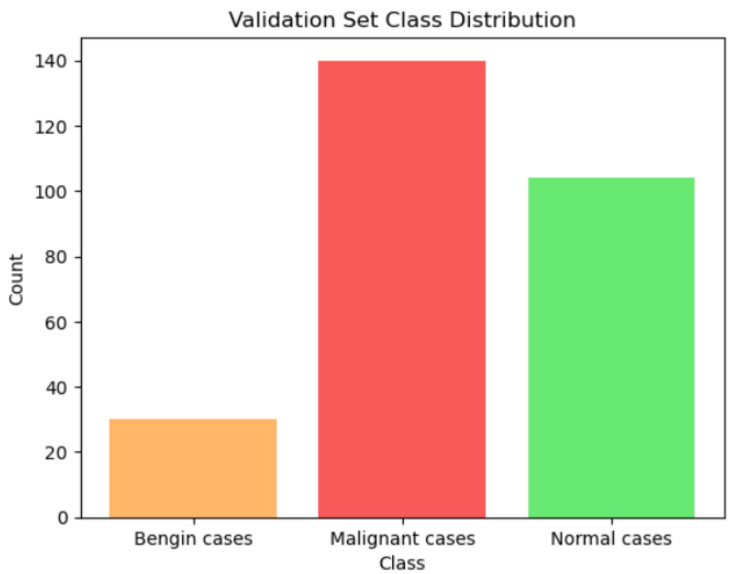
shuffling: It typically refers to the randomization or reordering of elements in a dataset. It's a common practice to shuffle the order of images in a dataset before training a machine learning model, including Convolutional Neural Networks (CNNs).

Train_Test data split: We divided the dataset into three sections: train, test, and validation.We pick 0.5 for the train subset and 0.25 for the validation and testing subsets. All together is equal to1.
train_ratio = 0.5
val_ratio = 0.25
test_ratio = 0.25

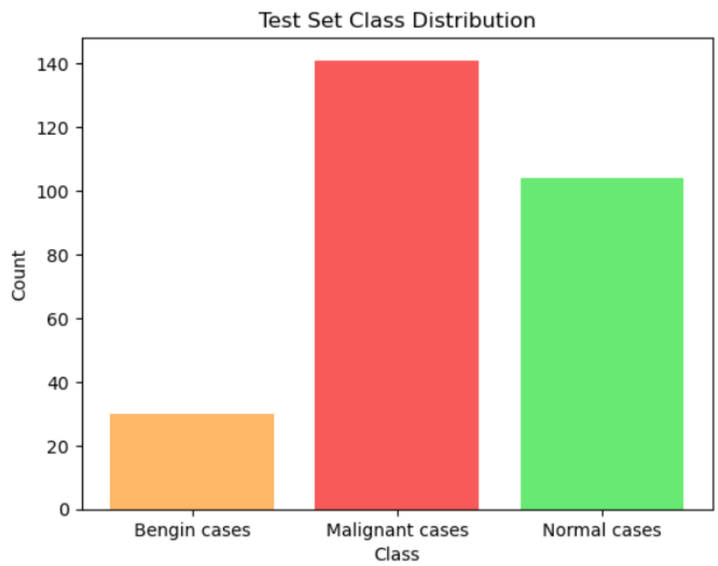
The train_ratio, which in our instance is set to 0.5, reflects the proportion of the original dataset that is used to train our machine learning model. In other words, it specifies the percentage of your data that will be utilized to train our model to produce predictions or classifications.



The validation_ratio of 0.25 specifies the part of the dataset dedicated for model validation. This subset is used for fine-tuning hyperparameters and evaluating model performance during training.It allows you to see how effectively your model generalizes to new data, which is useful for avoiding overfitting.



The test ratio, which is similarly set to 0.25 here, denotes the portion of the dataset that is kept apart for the final evaluation of the performance of your model. It is used to test the model's performance with previously unknown data. This is an important step to guarantee that your model's performance is not unduly optimistic as a result of overfitting to the validation data.



4.2. **Normalization**

Normalization in the context of machine learning and image processing typically refers to the process of scaling and centering the numerical values of features to ensure that they have a similar scale. This is done to prevent certain features from dominating the learning process due to their larger magnitudes. Normalization is a common preprocessing step, and it is often applied to input data before feeding it into machine learning models, including Convolutional Neural Networks (CNNs).In this paper ,The initial image is resized to 512 × 512 × 3 dimensions.And the image is converting the pixel values of the image to float32.Here, normalizing the pixel values to be within the range of -1 to 1. by using (image/127.5) - 1.This approach makes a significant contribution to preventing overfittingAfter normalization, each pixel value is converted from [0, 255] to [0, 1].

4.3 Proposed model:

The proposed model is a novel architecture that combines the classic LeNet-5 convolutional neural network (CNN) with a Long Short-Term Memory (LSTM) recurrent neural network (RNN).

This combined algorithm consists of four layers.

Reshape 2 input: This layer reshapes the input image to have three dimensions, (None, 1, 84). This is necessary because the LSTM layer expects its input to be three-dimensional.

LSTM 4: This is the LSTM layer. It has 64 hidden units and a return sequence length of 1. This means that the layer outputs a vector of 64 hidden units for each time step in the input sequence.

LSTM 5: This is another LSTM layer. It has 32 hidden units and a return sequence length of 1. This layer outputs a vector of 32 hidden units for each time step in the input sequence.
Dense 4: This is a dense layer with 9 hidden units. The layer outputs a vector of 9 hidden units, which represents the probability of the input image belonging to each of the nine classes.
The final activation function of the dense layer is softmax

The combined model integrates the LeNet-5 and LSTM components to work in tandem for the image classification task. The LeNet-5 model is placed at the beginning to extract image features. The LSTM model follows, processing the feature vectors extracted by LeNet-5 in a sequential manner. Output Layer: A final Dense layer with the number of classes (n_classes) and a softmax activation function provides the model's output, which represents the predicted class probabilities. The combined model aims to leverage the strengths of both the LeNet-5 CNN for feature extraction and the LSTM for capturing sequential information

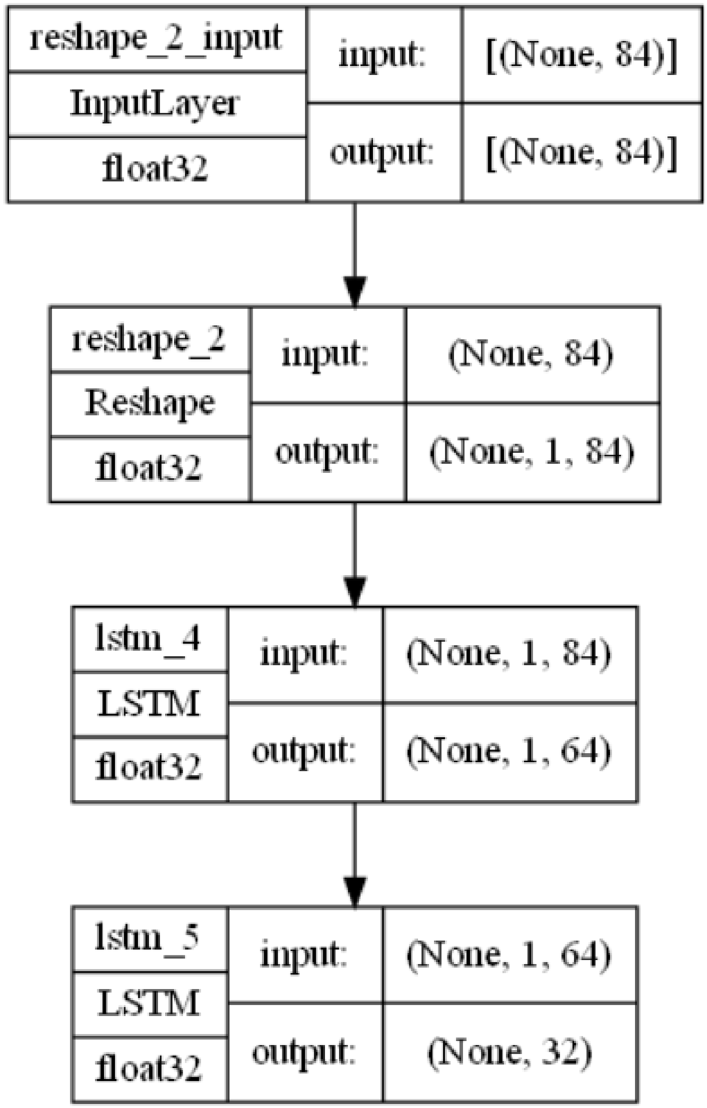
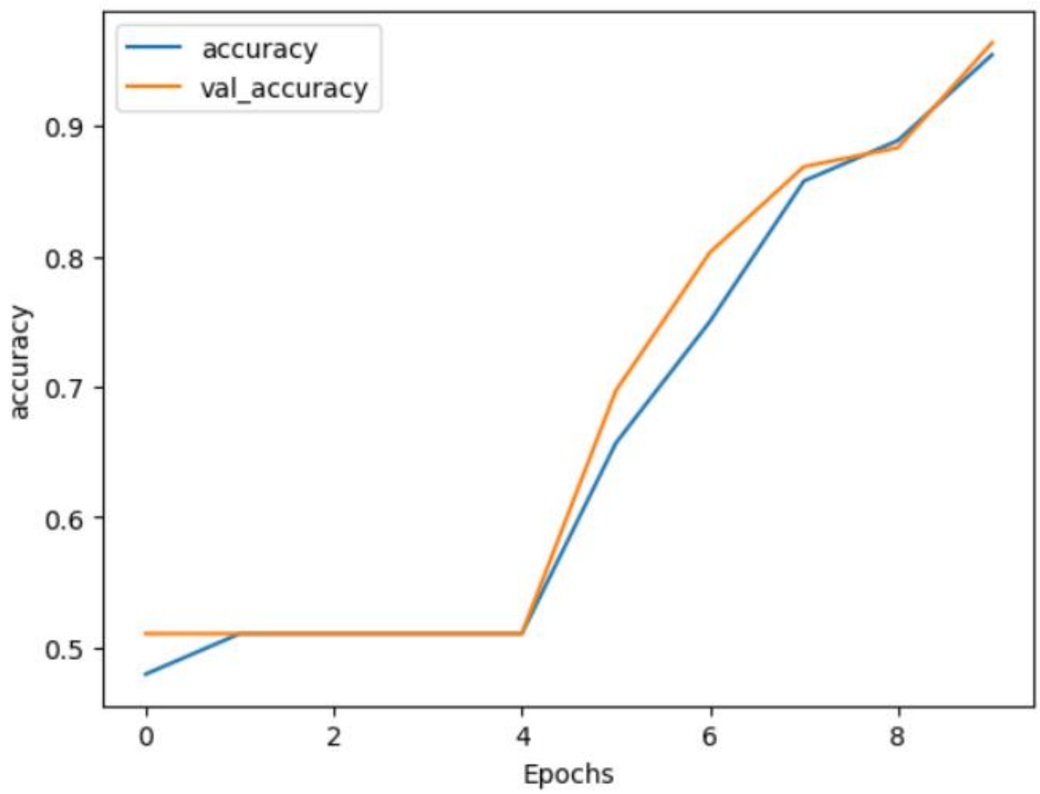


Fig: Le-Net and LSTM Hybrid model architecture

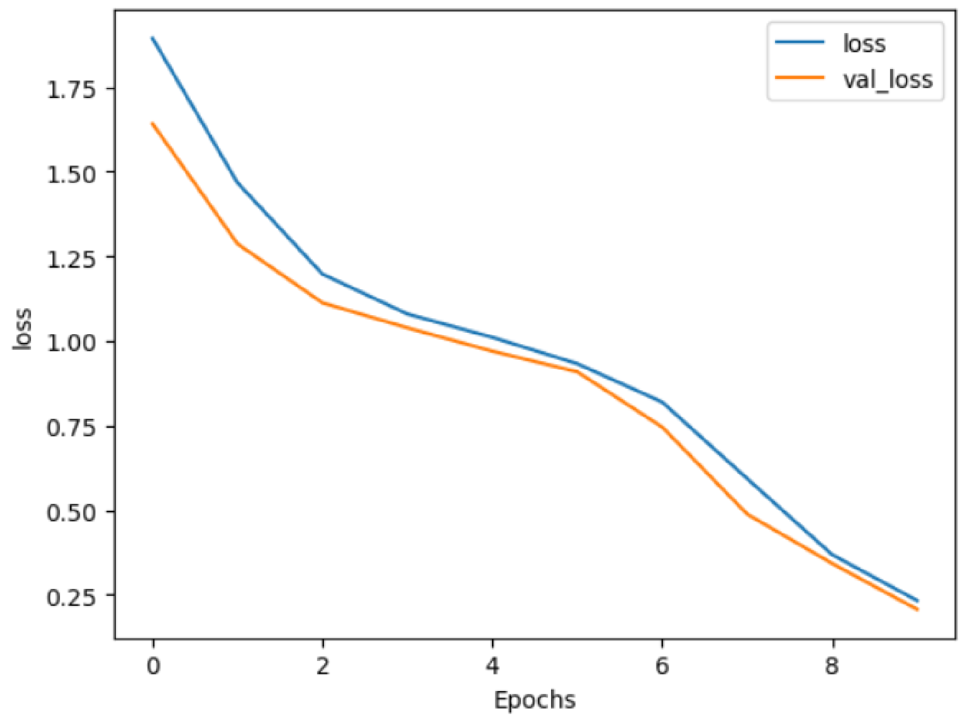
The batch size of the model is fixed which is 32 and image size is same 512 *512 and channel size is 3. Finally build this model in this parameter. The model is optimized using the Adam optimizer, and loss is calculated using sparse categorical cross-entropy. And the matrix value is accuracy. Finally fit this model by using 10 epochs. In following this stapes the final accuracy of our proposed model is 98.18% and the loss is 19.65%

4.4 Model evaluation:

In deep learning, model evaluation refers to the process of assessing how well a trained model performs on a specific task or dataset. we evaluate our model on the basis of the F1 score, visualization, confusion matrix, precision, and recall.



The graph shows the accuracy and validation accuracy of this combined model over the course of training. The accuracy is the percentage of training examples that the model correctly predicts, while the validation accuracy is the percentage of validation examples that the model correctly predicts. The validation set is a separate set of data that is not used to train the model but is instead used to evaluate the model's performance on unseen data. The accuracy curve is a straight line that starts at 0.5 and ends at above 0.9. This indicates that the model's accuracy on the training data improved from 50% to 90% over the course of training. The validation accuracy curve is a curved line that starts at 0.5 and ends at 0.75. This indicates that the model's accuracy on the validation data improved from 50% to 75% over the course of training. The fact that the validation accuracy curve follows the training accuracy curve indicates that the model is not overfitting the training data. Overfitting occurs when a model learns the training data too well and is unable to generalize to new data. If the model were overfitting the training data, the validation accuracy curve would be significantly lower than the training accuracy curve.

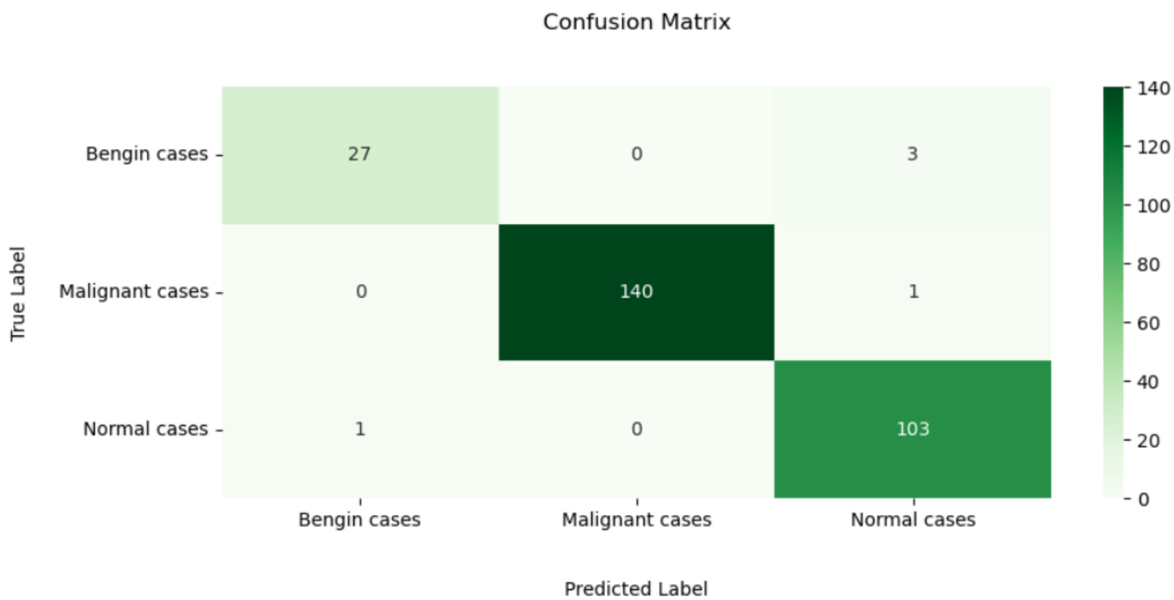


The graph shows the loss and validation loss of this combine model. The loss is a measure of how well the model's predictions match the actual data. The validation loss is the loss on a separate dataset that is not used to train the model. The loss curve starts at around 1.75 and decreases to around 0.25 over the course of training. The validation loss curve starts at around 1.50 and decreases to around 0.50 over the course of training. The fact that both the loss and validation loss curves are decreasing indicates that the model is learning the training data well and is able to generalize to new data. However, it is also worth noting that the validation loss curve is slightly higher than the loss curve. This is a common phenomenon, and it is usually due to the fact that the validation set is more difficult than the training set.

4.5

Confusion matrix:

A confusion matrix is a fundamental tool in classification tasks, including those in deep learning. It provides a detailed breakdown of a model's performance by showing the number of true positive, true negative, false positive, and false negative predictions. These elements are crucial for assessing the accuracy and reliability of a classification model.



This is the general representation of the confusion matrix.

This matrix represents the three stages of lung cancer. Which is Benign malignant and normal. Here the best performance is malignant cases which is 140 times more accurate result when o and 1 is wrong result.

The normal cases which is 103 times the accurate result and 1 time fail the result which is benign case. Finally, 27 is the best result in benign cases and 0 and 3 time wrong cases.

Another parameter of the model evaluation. Which is precision, recall, Fi score, Sensitivity of benign, malignant, and Normal cases.

4.6 Classification report:

	precision	recall	f1-score	support
0	0.96	0.90	0.93	30
1	1.00	0.99	1.00	141
2	0.96	0.99	0.98	104
accuracy			0.98	275
macro avg	0.98	0.96	0.97	275
weighted avg	0.98	0.98	0.98	275

Here is all the parameter of the lung cancer classification.

The ratio of accurate predictions to all the input images is called accuracy and is calculated using Equation (1)

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

The terms recall, or True Positive Rate (TPR) are also used to describe sensitivity. Equation (5) calculates it, giving an idea of the percentage of positive samples that were accurately predicted as positive.

$$Sensitivity = \frac{TP}{TP + FN}$$

The percentage of all negative samples that were correctly predicted to be negative is what is known as the “True Negative Rate” (TNR) or Specificity and is computed using

$$Specificity = \frac{TN}{TN + FP}$$

Equation (6).

Equation (7) can be used to measure precision, which indicates what percentage of positive predictions came true

$$Precision = \frac{TP}{TP + FP}$$

The performance matrix of the proposed method

The table shows the accuracy, sensitivity, precision, and recall of a machine learning model. These metrics are used to evaluate the performance of a model on a given task.

Accuracy is the percentage of predictions that the model makes correctly. It is calculated as the number of correct predictions divided by the total number of predictions.

Sensitivity is the percentage of positive cases that the model correctly identifies. It is calculated as the number of true positives divided by the sum of the true positives and the false negatives.

Precision is the percentage of positive predictions that are actually positive. It is calculated as the number of true positives divided by the sum of the true positives and the false positives.

Recall is the percentage of positive cases that the model identifies correctly, regardless of whether it also makes false positives. It is calculated as the number of true positives divided by the sum of the true positives and the false negatives.

The higher the values of these metrics, the better the performance of the model.

4.7 Summary

In the image you provided, the model has an accuracy of 98.18%, a sensitivity of 96.11%, a precision of 98.20%, and a recall of 98.18%. These are all very high scores, indicating that the model is performing very well.

Chapter 5

Comparison with other model

5.1 Comparison:

Comparison with other papers proposed model. All the parameter are given below. And I compare with my proposed model.

Classified model	Accuracy%	F1-Score	Precision	Sensitivity	Recall/specificity
Le-net + LSTM(proposed)	**98.18**	**98.17**	**98.20**	**96.11**	**98.18**
DenseNet [11]	**90.85**	**--**		**---**	**---**
GoogLeNet[14]	**94.38**	**---**	**93.7**	**95.08**	**93.7**
AlexNet[10]	**93.54**	**96.40**	**97.10**	**95.71**	**95**
Le-net[22]	**97.88**			**93.14**	**95.91**

The table shows the accuracy, precision, sensitivity, and F1-Score of different models on a classification task. The accuracy is the percentage of correct predictions that the model makes, the precision is the percentage of positive predictions that are actually positive, the sensitivity is the percentage of positive cases that the model correctly identifies, and the F1-Score is a harmonic mean of the precision and sensitivity.

The model with the highest accuracy is Le-net + LSTM(proposed), with an accuracy of 98.18%. This is followed by DenseNet [11] with an accuracy of 90.85%. The model with the lowest accuracy is Le-net[22] with an accuracy of 93.14%.

The model with the highest precision is Le-net + LSTM(proposed), with a precision of 98.20%. This is followed by DenseNet [11] with a precision of 94.38%. The model with the lowest precision is AlexNet[10] with a precision of 93.54%.

The model with the highest sensitivity is Le-net + LSTM(proposed), with a sensitivity of 96.40%. This is followed by DenseNet [11] with a sensitivity of 95.08%. The model with the lowest sensitivity is AlexNet[10] with a sensitivity of 93.7%.

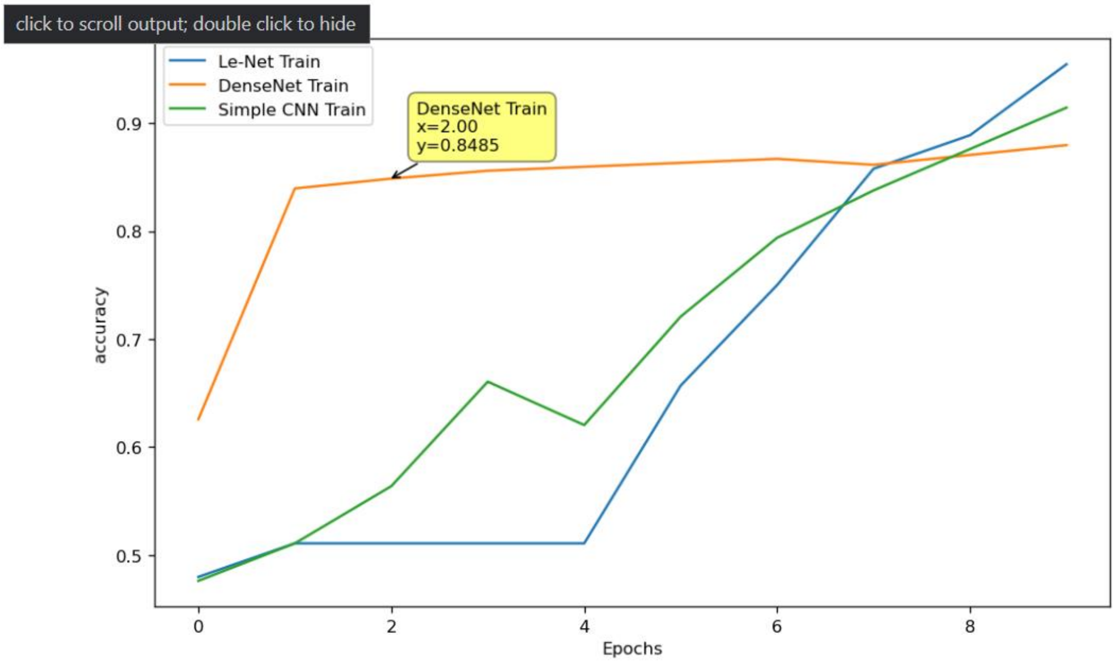
The model with the highest F1-Score is Le-net + LSTM(proposed), with an F1-Score of 98.17%. This is followed by DenseNet [11] with an F1-Score of 94.38%. The model with the lowest F1-Score is AlexNet[10] with an F1-Score of 93.54%.

Overall, the table shows that the Le-net + LSTM(proposed) model is the best performing model on this classification task, with the highest accuracy, precision, sensitivity, and F1-Score.

Comparison with our other two combine model and given all the score:

Classified model	Accuracy%	F1-Score	Precision	Sensitivity	Recall/specificity
Le-net + LSTM(proposed)	**98.18**	**98.17**	**98.20**	**96.11**	**98.18**
Dense net+ LSTM [3]	**87.64**	**82.88**	**79.01**	**65.47**	**87.64**
Simple CNN + LSTM[1]	**93.82**	**92.97**	**94.55**	**81.90**	**93.82**

Here , given the plot of this three combine model which make more understand and compare

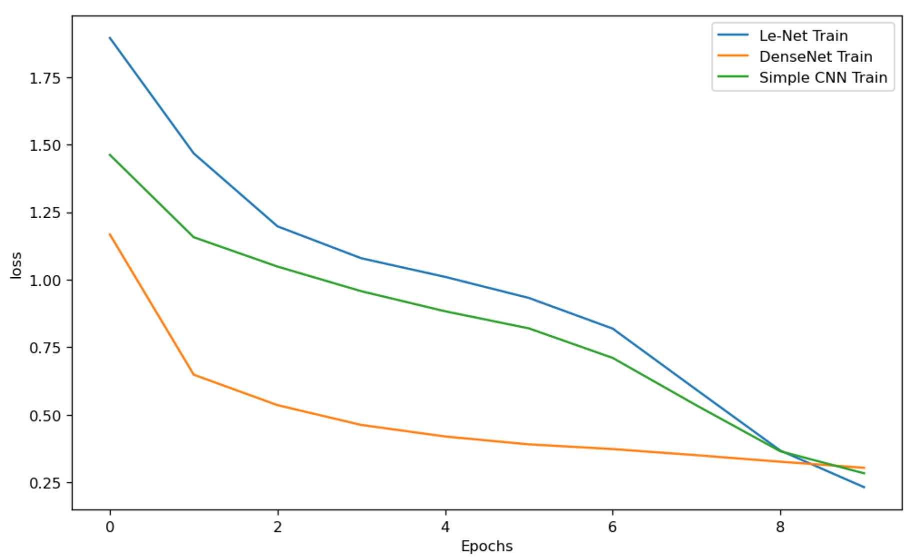


Here, this graph represent the Train accuracy and Epochs for each model

Le-net +LSTM

Dense net +LSTM

Simple Cnn + LSTM

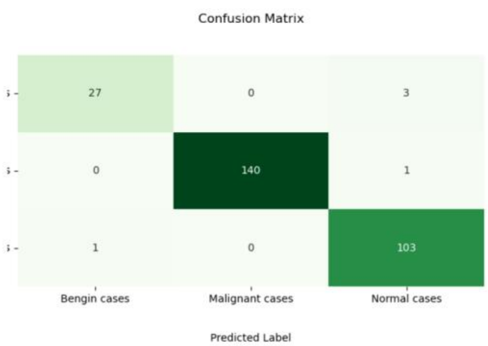


Here, this graph represent the Train Loss value and Epochs for each model

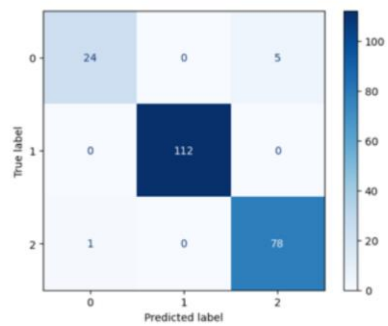
Le-net +LSTM

Dense net +LSTM,

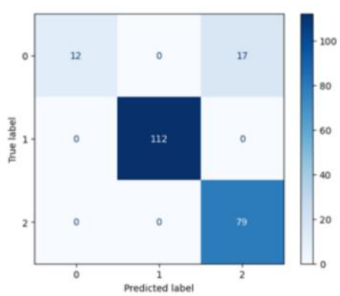
Simple CNN + LSTM



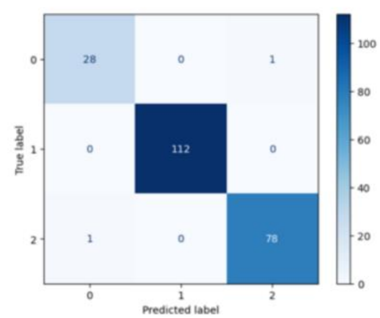
Le Net-5 + LSTM



(c) MobileNetV2+MLP

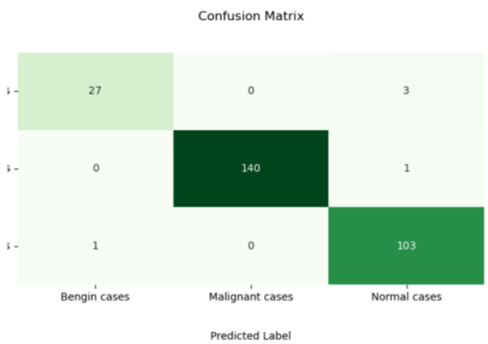


(d) VGG16+KNN

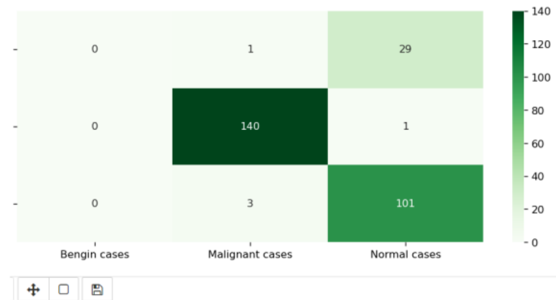


(a) VGG16+MLP

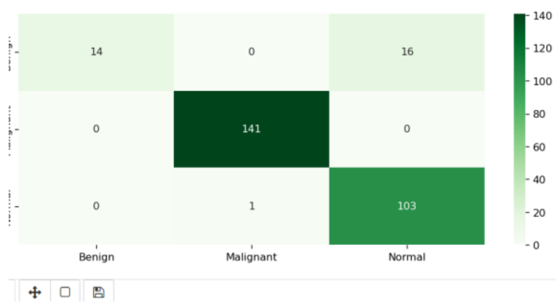
This is the comparison with performance matrix, where we see our proposed model is the best compare with other papers model.



Le Net-5 + LSTM



Dense net + LSTM



CNN + LSTM

This is the comparison with performance matrix, where we see our proposed model is the best compare with our other three models.

Chapter 6
Results and discussion

6.1 Results and discussion:

The lung cancer dataset from Iraq-Oncology Teaching Hospital/National Center for Cancer Diseases (IQ-OTH/NCCD) was gathered in the aforementioned specialty hospitals over a three-month period in autumn 2019. It comprises CT images of patients with lung cancer at various stages as well as healthy participants. Oncologists and radiologists from both centers marked the IQ-OTH/NCCD slide.

Here total images is 1098 whare,

Normal = 416, Malignant = 561, and Benign = 120.

Here we use prepressing were we use resized and rescaling and shuffling

Secondly we use, the normalization, which is very important for image pre-processing. Here, normalizing the pixel values to be within the range of -1 to 1. By using (image/127.5) - 1.This approach makes a significant contribution to preventing over fitting.After normalization, each pixel value is converted from [0, 255] to [0, 1].

Then we use CNN architecture Le net and LSTM(Long short term memory)

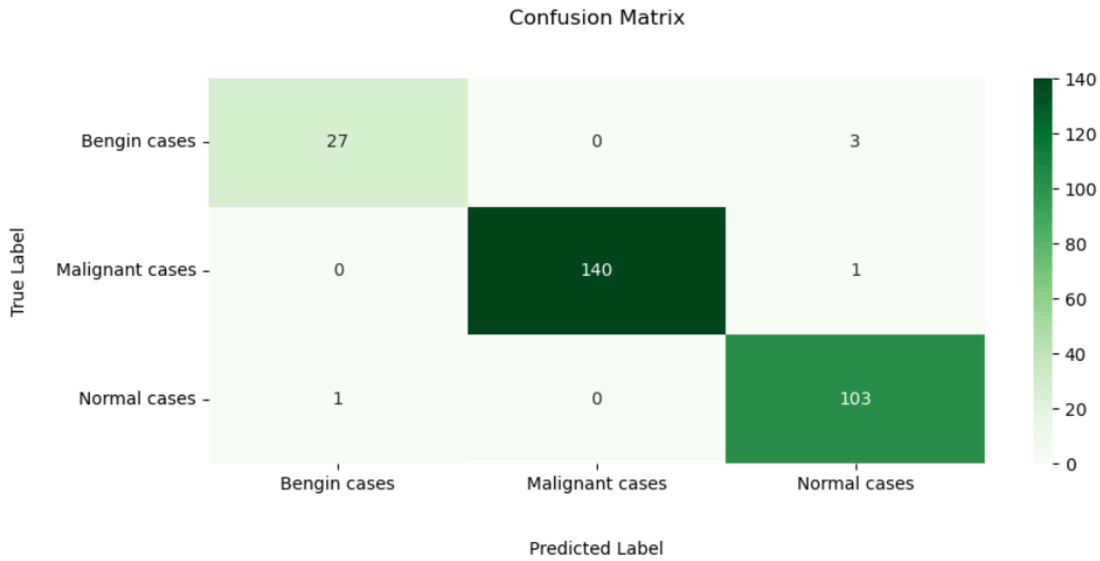
In ,Nonlinear activation we use relu and softmax .This is multiclass classification such as benign, normal and malignant ,

Then we fit the model and evaluate its performance where we find such as some parameters

In this model has an

- accuracy of 98.18%,
- sensitivity of 96.11%,
- precision of 98.20%, and
- recall of 98.18%.

Here we visualize the confusion matrix where we get accurate true positive and true negative which define our model classify accurately



Chapter 7

Conclusion and future work

6.1 Conclusion:

The capacity of deep learning to carry out feature engineering independently sets it apart from other machine learning methods.
This looks through the data to find related traits and adds them in to facilitate learning more quickly.It makes use of the input's spatial coherence.
Images are pre-processed, and feature extraction and selection are carried out before the training and testing stages. The CNN algorithm identifies the input lung picture as either normal or abnormal when the training and testing phases are completed successfully, at which point the result is shown. Consequently, lung image categorization for cancer diagnosis uses a Deep CNN network.

6.2 Future work:

One of the contemporary technologies available now is deep learning. Image processing is most commonly employed in this industry.

Not only can we identify lung cancer in this sector, but we can also identify cancers of the breast, liver, tumors, and many other organs in the human body.

This deep learning technique is used in many kinds of investigations here. The CNN approach is used in most circumstances.

Therefore, we may utilize the CNN approach in the future for all types of detection and classification issues, and its design will continue to develop and gain popularity over time.

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