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Diagnosis of Tobacco Related Organ Cancers

Pathmapriya N, Pooja R

Department of Information Technology, Rajalakshmi Engineering College (REC), Chennai, Tamil Nadu, India

ABSTRACT
This paper titled "Diagnosis of Tobacco-Related Organ Cancers" addresses the critical issue diagnosing Tobacco-Related organ cancers in the human body, by which the majorly affected organs were lung, colon and oral regions, thar are mainly affected due to a high level of tobacco usage. This project uses a Convolutional Neural Network (CNN) algorithm for the accurate detection of these cancers. Various essential metrics were used to evaluate the model's performance. A web application was also developed to enhance the accessibility and usability, allowing the users to upload medical result images like histopathological images. This application provides a real-time assessment indicating the presence or absence of cancers, thus empowering an individual to make informed decisions. This integrated approach holds great promise for early cancer diagnosis and management, addressing the public health concerns regarding tobacco-related organ cancers.

KEYWORDS
Tobacco; Convolutional Neural Network (CNN); Histopathological Images (HI); Web Application.

1. INTRODUCTION

Tobacco usage remains one of the most global health concerns, causing the huge number of deaths across the world. According to WHO, more than 8 million people were died by using tobacco in all over the world during 2023. Due to a high usage of tobacco by the people, the organs like lung, colon and oral regions gets damaged, and the cancer cells gets spread across the organs causing the organ failure or the cancer tumor in these organs of the human body. These cancers collectively represent some of the most prevalent and deadly cancers worldwide, necessitating urgent attention to improve their early detection and intervention. Developing a user friendly and interactive web application for diagnosing these cancers is one of the most efficient solutions for early diagnosis. In the proposed system project uses a Convolutional Neural Network (CNN) algorithm, like Xception Net, Manual Net and LeNet architectures are highly effective in identifying the patterns and distinguishing features within medical images.

A. BACKGROUND AND MOTIVATION

The major problem concerning global health is organ cancers associated with smoking. Currently, the diagnostic process is not uniformed, instead it relies on separate AI models for lung, colon and oral cancers indicating the need for a single solution. By developing an integrated AI model that will boost early detection and improve patient outcomes, our goal is to make diagnostic more efficient and thus contribute to global health.

B. BACKGROUND MOTIVATION

The present approach for diagnosing organ cancers related to smoking involves the use of all kinds of AI modes for lung, colon and oral cancers, thus causes inefficiencies. The Streamlined diagnostic, impeded by the non-uniform system, require the establishment of a single AI model that will help to improve efficiency, prevents the early detection in addition to contributing towards global health agendas.

C. OBJECTIVES

- This project's main objective is to come up with diagnostic results that the person can be understood even by those who do not have a medical background.
- To enable independent understanding, this project will develop user-friendly interface. At the same time, there will be a greater emphasis on improving early cancer detection using advanced algorithms.
- The overall objective is to enhance personal realization as well as the contribution towards bettering of the healthcare system.

2. LITERATURE REVIEW

This comprehensive literature survey evaluates the diverse facts of diagnosis of tobacco related cancers at an early stage. The authors in [1] discusses that the Tobacco-related organ cancer is a significant health concern. Lung cancer is commonly diagnosed malignancy with high mortality rates, that is classified into two major classes of lung cancer. In [2] Oral Squamous cell carcinoma (OSCC) is another type of cancer that has been extensively studied in terms of its histopathological features and impact on prognosis and treatment planning.

The authors in [3] has discussed about the historical evolution of oral cancer has revealed the evolution of its management. This paper [4] presents a deep understanding about in Oral microbiota that are all related to lung diseases, including pneumonia and chronic lung infections. In [5] Synchronous occurrence of lung and oral

cancers have also been observed, and treatment and outcomes of the patients with both cancers have also been reviewed. The authors in [6] highlighted the importance of considering gastrointestinal Metasys in lung cancer patients presenting with symptoms, such as refractory iron deficiency and colon lesions. It includes computed tomography (CT) scans of the chest, pelvic and abdomen that were used to detect metastatic lesions in the colon and other distant sites. The authors in [7] this paper proves the thorough study for the determinant that causes oral cancer in the human body, contributing to the understanding of the various factors that causes oral cancer in the human body. They highlighted that the contented action may arise due to high usage of marijuana and, also due to genetical disorder.

The authors in this paper [8] discusses that the process of examination of oral is used as a non-invasive approach for the detection of these cancers that are accumulated in lung area. They also specified the evolution of a cell-based detector also known as the lab on a chip detector which utilizes an embedded track-etched layer to capture cutis from brush cytology.

The authors in [9] discusses that cancer is the dominant and dreadful illness as it grows immediately in humans when it is not treated well in the initial stages. Most of the lung cancer were caused due to the-effect of smoking. Most of the cancers produces the consequence from out-of-control duplication of cells which lose the capacity to effectively manage genomic material. Colorectal cancer is a major cause of cancer-related death, with a wide geographic variation in incidence. Lung cancer is diagnosed using various diagnostic techniques such as chest radiography, sputum analysis, PET, Magnetic Resonance Imaging (MRI) and blood tests.

The paper [10] gives a singular 3-d Deep Convolutional Neural network (3DDCNN) for diagnosing the lung cancer that uses CT chest scan picture. This model's fundamental motive is to assist the radiologist. Through appearing a guide delineation of lung nodules is a large task. So, to reduce the workload for the radiologist this model is advanced. This CAD model is skilled and examined using numerous datasets like ANODE09, and LIDC-IDR and produces an accuracy of 98%. This version is likewise established the usage of cloud primarily based dataset images supplied with the aid of Shanghai sixth people's hospital.

This paper [11] proposes a novel technique for diagnosing the small lung cancer cells in human thorax models. This model can be able to diagnosing the lung the lung most cancer cells which might present within the human body and it additionally as it should define the scale of the most cancers mobile and in which its far placed in human frame. The paper [12] proposes a completely unique method for oral cancers discovering and dissection the usage of nanotechnology. The authors have utilized the numerous nanotechnology, based on absolutely discovering and prognosis floor plasmon resonance scattering and lots of others including that the small and untimely intraepithelial lesions can be unnoticed by common place techniques can probably be detected with the aid of the usage of nano-technologies [13]-[17].

3. DATASET

The Datasets for the proposed system model were taken from the data.gov website that is maintained by US government with the sample image sets of lung, colon, and oral cancers to classify whether the affected person discloses any of these cancers. There are 7 classes: The first 3 classes classify lung cancer as stage-1, stage-2, or normal conditions. The next classes classify colon cancer as colon cancer present or normal conditions. The last two classes classify oral cancers present in the human body or normal conditions. This unique dataset contains 7000 RGB-colored histopathological images, which are resized into 224 x 224 pixels. The table I represents the sample dataset images of lung, colon, and oral cancers.

Table 1. Sample Dataset Images

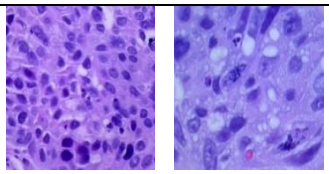
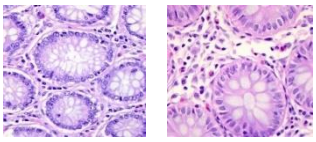
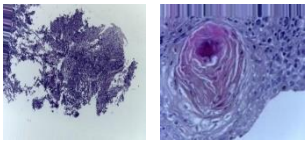
Type of Cancer	*Histopathological Images*
Lung Cancer	
Colon Cancer	
Oral Cancer	

Table 2 shows System components and Specifications.

Table 2. System components and Specifications

System Components and Specifications		
Component	***Description***	***Specification***
Windows OS	Compatible with software versions to ensure widespread accessibility.	Windows OS versions: 7,8,10
Anaconda	An Environment where the Machine Learning Model is developed	Jupyter NoteBook, Libraries: Keras, TensorFlow,Matplotlib.
Django	A Web Framework Technology for connecting the ML model with Frontend.	CPU: Intel Core i5-4400E RAM: 8GB, File Size: 3 GB OS: Windows 10.

System Components and Specifications		
Component	***Description***	***Specification***
Backend Server	Cloud-based server for data processing, storage, and user authentication.	Processor: Dual-core Xeon RAM: 16GB, Storage: 1TB, Communication: Wi-Fi
Database	Storage for user profiles, access logs, sentiment analysis results and other relevant data	Database Type: MySQL Storage Capacity: 500GB Backup and Replication

4. MANUALNET ARCHITECTURE

The Manual Net architecture refers to a customized model where each layer is customized and implemented using python and TensorFlow framework. This includes adjusting the parameters and configurations of several layer to optimize the performance. Subsequently, this model is trained and tested under the given datasets containing lung, colon, and oral cancers and producing the accuracy of 95 percentage. This model contains sever layers and their functionalities were discussed [18]-[19].

A. Conv2D Layer

The convolutional layer is a fundamental operation in an image processing. It involves making use of a filter to an input image to extract specific features. It is done via sliding the filter over the image and computing the element wise product and sum of the overlapping regions. Mathematically, it is represented as:

$$(I*K)(i,j)=\sum m\sum nI(m,n)\cdot K(i-m,j-n) \quad (1)$$

Where I is the image, K is the clearout (moreover called kernel), and (i,j) are the pixel coordinates.

B. Activation Layer (ReLU)

The Rectified Linear Unit (ReLU) is an activation function that introduces non-linearity to the network. It computes the maximum between zero and the input value. Mathematically, it is represented as:

$$f(x)=max(0,x) \quad (2)$$

C. MaxPool2D Layer

This layer performs max pooling operation on the input tensor to lessen its spatial dimensions. The mathematical equation for this layer is:

$$MaxPooling(x) = max(i,j)\in Window\ x(i,j) \quad (3)$$

Where x is the enter tensor and Window is a chosen window size.

D. Flatten Layer

The flatten layer condenses the output from convolutional and pooling layers right into a one-dimensional array, facilitating seamless connection to fully linked layers. This transformation lets in the community to technique spatial data extracted from input images successfully, serving as a pivotal bridge among characteristic extraction and prediction stages.

E. Fully Connected Layer

A fully Connected Layer is also called as Dense Layer is a neural network layer where each neuron is connected to every nin the previous layer. It applies a linear transformation followed by an activation function. Mathematically, it is represented as:

$$h=\sigma(Wx+b) \quad (4)$$

Where h is the output, W is the weight matrix, x is the input vector, b is the bias vector, and σ is the activation function.

The Manual Net CNN model produces an accuracy of 95 percent during the training and testing of the given dataset and implemented using python and TensorFlow framework. The given Figure 1 is the graph of the model accuracy of Manual Net Architecture.

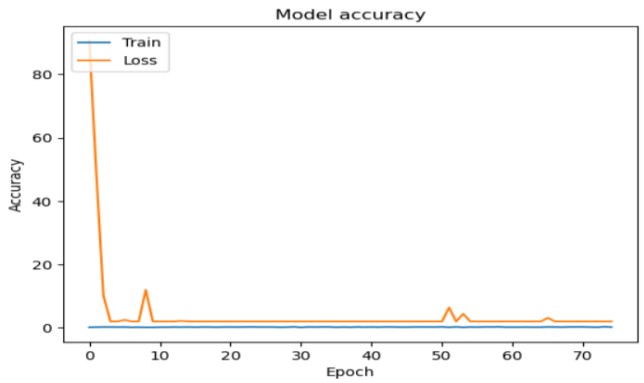


Fig. 1. Model Accuracy for Manual Net Architecture

5. XCEPTIONNET ARCHITECTURE

The XceptionNet architecture makes use of several varieties of layers including Conv2D, Batch Normalization, ReLU, MaxPool2D, SeparableConv2D, Add, GlobalAvgPool2D, Dense layer and it is implemented using Python and TensorFlow framework. This model is trained and tested using the given datasets and it produces an accuracy of 80 percentage during the training and testing of the model.

A. Conv2D Layer

The convolutional layer is a fundamental operation in an image processing. It involves making use of a filter to an input image to extract specific features. It is done via sliding the filter over the image and computing the element wise product and sum of the overlapping regions. Mathematically, it is represented as:

$$(I*K)(i,j)=\sum m\sum nI(m,n)\cdot K(i-m,j-n) \quad (1)$$

Where I is the image, K is the clearout (moreover called kernel), and (i,j) are the pixel coordinates.

B. Batch Normalization Layer

This layer normalizes the activations of the previous layer to enhance the schooling pace and regularization. Mathematically, it is represented as:

$$y(i,j) = \gamma * \text{fracx}(i,j) - E[x]\text{sqrtVar}[x] + \varepsilon + \beta \quad (5)$$

Where x is the input tensor, y is the output tensor, E[x] is the mean of x, Var[x] is the variance of x, y and β are learnable parameters, and ε is a small steady added for numerical balance.

C. Activation Layer (ReLU)

The Rectified Linear Unit (ReLU) is an activation function that introduces non-linearity to the network. It computes the maximum between zero and the input value. Mathematically, it is represented as:

$$f(x)=\max(0,x) \quad (2)$$

D. MaxPool2D Layer

This layer performs max pooling operation on the input tensor to lessen its spatial dimensions. The mathematical equation for this layer is:

$$\text{MaxPooling}(x) = \max(i,j)\in\text{Window } x(i,j) \quad (3)$$

Where x is the enter tensor and Window is a chosen window size.

E. SeperableConv2D Layer

The SeperableConv2D Layer plays a depthwise separable convolution operation on the input tensor with a special style of filters, kernal length, and padding. It first performs a depthwise convolution observed through the use of pointwise convolution. The mathematical equation for this layer is:

$$(I*K)(i,j)= \sum m \sum n\ I(m,n)\cdot K(i-m,j-n) \quad (6)$$

Where I is the input tensor, K is the filter out (additionally known as kernel), and (i,j) are the special coordinates.

F. Add Layer

This Add Layer adds the entered tensors element-clever. The Mathematical equation for this layer is:

$$y = x1 + x2 \quad (7)$$

Where x1 and x2 are the input tensors.

G. GlobalAvgPool2D Layer

The GlobalAvgPool2D layer performs worldwide average pooling on the entered tensor to lessen its spatial dimensions to 1x1. The mathematical equation for this layer is:

$$\text{GlobalAvgPool2D}(x) = 1/W * 1/H\ \Sigma\ i\ \Sigma\ j\ x(i,j) \quad (8)$$

Where x is the entered tensor, W and H are the spatial dimensions of x.

F. Fully Connected Layer

A fully Connected Layer is also called as Dense Layer is a neural network layer where each neuron is connected to every neuron in the previous layer. It applies a linear transformation followed by an activation function. Mathematically, it is represented as:

$$h=\sigma(Wx+b) \quad (4)$$

Where h is the output, W is the weight matrix, x is the input vector, b is the bias vector, and σ is the activation function.

In the XceptionNet Architecture, these layers are used to create an access go with the entry flow, middle flow and exit flow. The entry flow consists of several layers like Conv2D, BatchNormalization, ReLU and MaxPool2D layers, accompanied by the usage of numerous SeperableConv2D, Add and ReLU layers. The middle layer includes several SeperableConv2D, Add and ReLu layers. The exit flow includes several SeperableConv2D, ReLU, GlobalAvgPool2D and Dense layers. These flows are combined to create the final output tensor. This architecture produces 80 percentage accuracy during the training and testing of the given dataset images. This model suprases the ManualNet architecture model over the training and testing under the given datasets. The model Accuracy graph is shown in figure 2 as follows.

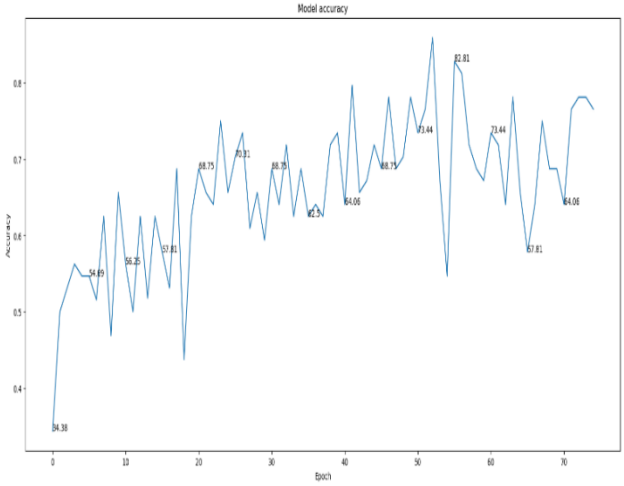


Fig. 2. Model Accuracy for XceptionNet Architecture

6. LENET ARCHITECTURE

LeNet is a predefined architecture which has the small structure, and it includes the essential layers like other CNN learning models. It is an easy and essential architecture model for other CNN learning models. It contains the layers like Conv2D layer, Average pooling layer and Dense layer. It also applies the softmax as an activation function. Subsequently, this model is trained and tested under the given datasets containing lung, colon, and oral cancers and producing the accuracy of 40 percentage. The functionalities of these layers were discussed below.

A. Conv2D Layer

The convolutional layer is a fundamental operation in an

image processing. It involves making use of a filter to an input image to extract specific features. It is done via sliding the filter over the image and computing the element wise product and sum of the overlapping regions. Mathematically, it is represented as:

$$(I*K)(i,j)=\sum m\sum n I(m,n)\cdot K(i-m,j-n) \quad (1)$$

Where I is the image, K is the clearout (moreover called kernel), and (i,j) are the pixel coordinates.

B. AvgPool2D Layer

This layer performs average pooling operation on the input tensor to lessen its spatial dimensions. The mathematical equation for this layer is:

$$\text{AvgPooling}(x) = \text{avg}(i,j)\in\text{Window } x(i,j) \quad (9)$$

Where x is the enter tensor and Window is a chosen window size.

C. Fully Connected Layer

A fully Connected Layer is also called as Dense Layer is a neural network layer where each neuron is connected to every nin the previous layer. It applies a linear transformation followed by an activation function. Mathematically, it is represented as:

$$h=\sigma(Wx+b) \quad (4)$$

Where h is the output, W is the weight matrix, x is the input vector, b is the bias vector, and σ is the activation function.

The LeNet CNN model produces an accuracy of 40 percentage during the training and testing of the given dataset and it is implemented using python and Tensorflow framework. This derived accuracy is lower compared to rest of the architecture models. The comparison of these three models like ManualNet, XceptionNet and LeNet were discussed in Table 3. The Figure 3 is the graph of the model accuracy of LeNet Architecture.

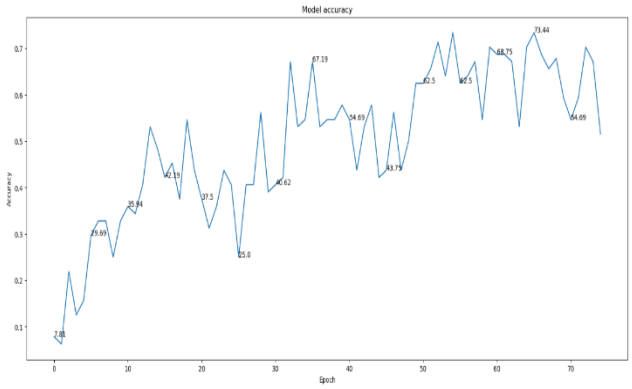


Fig. 3. Model Accuracy for LeNet Architecture

D. Performance Measure

The performance of the model is measured under the accuracy efficiency. In LeNet Architecture, the accuracy generated by the given model during the training and testing of the given dataset is 40%. In XceptionNet Architecture, the accuracy generated by this model us 80 % which is higher than Manual Net CNN. But in Manual Net Architecture the accuracy generated by this model is 95% which is higher than those two models. By comparing these three models, the Manual Net architecture is considered as a base model for the proposed system project. The Table 3 discusses the accuracy comparison between three models.

Table 3. Accuracy comparison between three models

Parameter	*ManualNet Architecture*	XceptionNet Architecture	LeNet Architecture
Batch size	1024	1024	1024
Epos	75	75	75
Accuracy (%)	95	80	40

7. DEPLOYMENT

In the deployment segment, Django Framework serves as the chosen device for deploying the model, in which the ManualNet Architecture serving as a Base Architecture Model. Through this framework, a user-friendly web application is created for the diagnosing tobacco related organ cancers at an early stage. The design of the website prioritizes simplicity, and easy to use, making the web application user friendly.

The following are the specifications of the proposed system's web application that ensures easy user access:

A. User Login

Each user must login into the web applications with their email ID and passwords that they have created. If it is a new user means then they have to create and account and then login into the application, then the user will be redirected to Home page screen.

B. Image Upload

After redirection to the Home page screen, the user can upload their medical result image in the web application, whereby the preview of the uploaded image is displayed on the webpage itself.

C. Result Webpage

The webpage shows a result message whether the cancer is present or not. Users may also view their usage history as well as the corresponding results that they have obtained during each session. The user can use the web application for multiple times that they want to use and can also view the history as well.

8. FLOWCHART

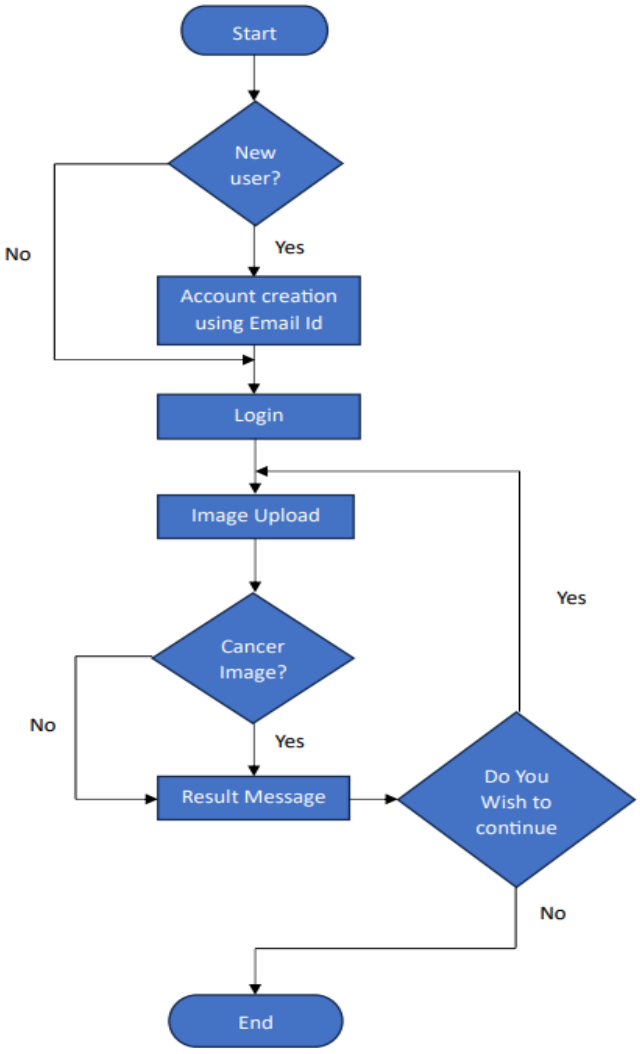


Fig. 4. Flowchart

Figure 4 shows the Flowchart.

9. RESULT AND DISCUSSION

The trained model classifies the Histopathological Medical Images as cancerous or non-cancerous cells in the organs like lung, colon and oral based on the trained dataset given to the model. The test data helps to validate the trained model. Comparing the three models, Manual Net Model has more accuracy than XCeptionNet model and LeNet model with 80% and 40% accuracy. The final model is saved and deployed using Django Framework. The path of the final module file is given to the deployment so that the image gets classified using that trained model. This project's main aim is to come with the diagnostic results that the person can be understood even the person does not have any prior medical knowledge. To enable independent understanding, the proposed system will have the user-friendly interface. This model can also be used as an AI Medical Aided Tool for cancer diagnosis in the Medical Field and Technology.

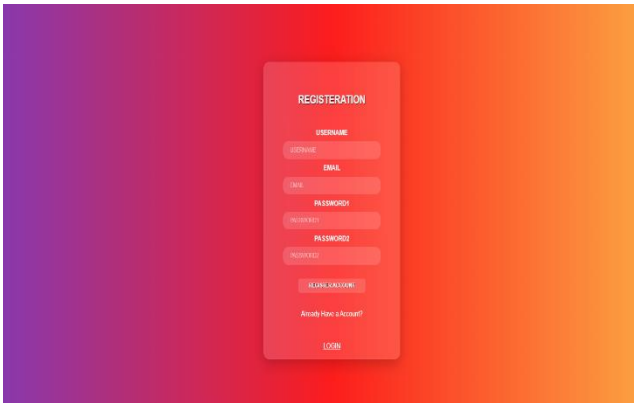


Fig. 5. Registration and Login Page

Figure 5 displays the registration and login page of the web application. If a person is a new-user then they need to register and login into the web application. After Login, it will redirect to home page **Figure 6.**

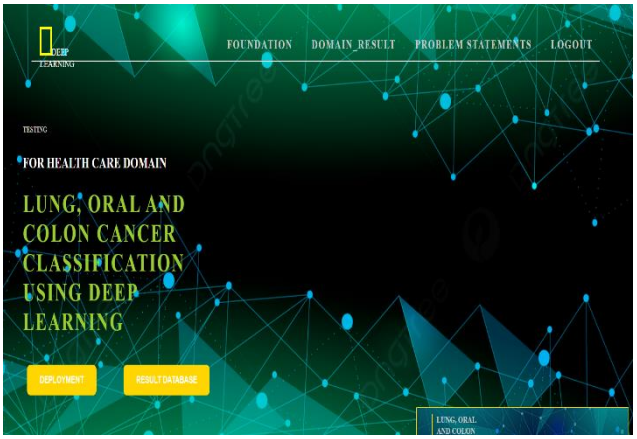


Fig. 6. Home page

Figure 6 displays the Home page of the proposed web application. In this home page, there are several options for viewing the problem statement, Domain Result, Founders of the project and the description of the proposed system implementation. There are few buttons for viewing the history database, and for deployment. Using the deployment button user can upload their result medical images of lung, colon and oral cancer.

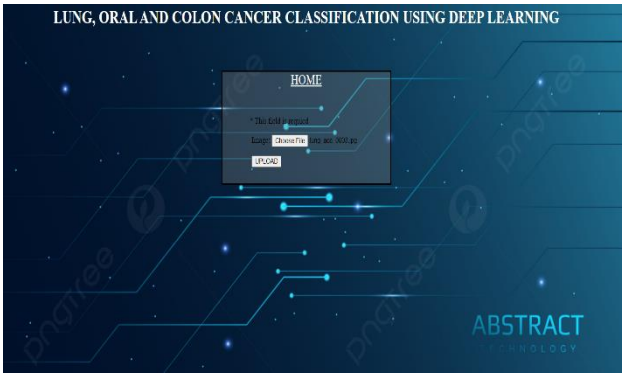


Fig. 7. Uploading the test image

Figure 7 displays the uploading page for the result image. Users can choose their result image from their computer and upload in this page.

Fig. 8. Result Page

Figure 8 displays the sample result page of lung cancer stage-1 prediction along with the causes and prediction of the lung cancer. The preview of the image is also attached at the bottom of the web page.

10. CONCLUSION

In the pursuit of addressing public health demanding situations of Tobacco-Related Organ Cancers encompassing lung, colon, and oral cancers, this challenge has developed a sturdy diagnostic framework powered with the aid of Convolutional Neural Network (CNNs). The model, incorporating critical overall performance metrics which include accuracy, sensitivity, and Area Under the Curve (AUC), demonstrates the capability to seriously enhance early cancer detection. Moreover, the creation of a user-friendly web application that allows the user to log into their account and they can upload their medical image regarding tobacco related organ cancer images like lung, colon and oral cancer images and can view their result in the web application itself without the need for any medical Knowledge or guidance. The web application is simple and easy to use, so that the patient regardless of their age can use this web application. So, from our methodology we conclude that this AI driven cancer diagnosis model can calculate accurately the results.

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Authors

Pathmapriya N received her BTech Information Technology degree from Rajalakshmi Engineering College (REC), Tamil Nadu, India in 2024. Her areas of interest are cybersecurity, Automation, Digital Forensics, cryptography and network security.

Email: priyachan2003@gmail.com

Pooja R received her BTech Information Technology degree from Rajalakshmi Engineering College (REC), Tamil Nadu, India in 2024. Her areas of interest are Web designing, and Automation in the UiPath Studio.

Email: Poojaramesh2901@gmail.com.