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Classifying Many Types of Cancer Using CT/MRI Images Based On Learning Without Forgetting -Powered Deep Learning Approaches

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Abstract: *In this research, we propose leveraging Artificial Intelligence (AI), specifically deep learning models, for the automated detection of various types of cancer, including lung, brain, breast, and cervical cancer. We employ Convolutional Neural Networks (CNNs) such as VGG16, VGG19, DenseNet201, MobileNetV3 (both small and large variants), Xception, and InceptionV3, utilizing transfer learning from pre-trained models like MobileNet, VGGNet, and DenseNet. Bayesian Optimization is employed to optimize hyperparameters, ensuring effective model performance. To address potential issues with transfer learning, we implement Learning without Forgetting (LwF), which preserves original network capabilities while enhancing classification accuracy on new datasets. Our experiments demonstrate superior accuracy compared to existing techniques, with MobileNet-V3 small achieving 86% accuracy on the Multi Cancer dataset. To further enhance performance, we explore prediction techniques using Xception and InceptionV3, aiming for an accuracy of 90% or higher. Additionally, we propose an extension to build a user-friendly front-end using the Flask framework, facilitating user testing with authentication. This research showcases the potential of AI-driven cancer detection, offering promising avenues for improved early diagnosis and treatment outcomes.*
INDEX TERMS *Cancer, convolutional neural network (CNN), pretrained models, Bayesian optimization, transfer learning, learning without forgetting, VGG16, VGG19, DenseNet, mobile net.*

I. INTRODUCTION

Cancer is a complex and pervasive disease that arises from abnormal cellular growth and proliferation, leading to potentially life-threatening consequences if left unchecked [1]. It stands as one of the most significant global health challenges, with its impact extending across all demographics and regions. According to recent statistics, cancer ranks as the leading cause of death worldwide, underscoring the urgent need for effective detection, diagnosis, and treatment strategies [2].

The origins of cancer are multifaceted, often stemming from a combination of genetic predisposition and environmental factors. Behavioral attributes such as high body mass index (BMI), tobacco and alcohol consumption, exposure to physical carcinogens like ultraviolet (UV) radiation, and ionizing radiation contribute significantly to cancer development [3]. Additionally, factors like chronic inflammation, infectious agents, and hormonal imbalances can influence carcinogenesis [4]. Consequently, the spectrum of cancer types is vast, affecting various organs and tissues in the body [5].

Among the common sites for cancer development are the lungs, breasts, brain, colon, rectum, liver, stomach, skin, and prostate [6]. Each cancer type presents distinct clinical features and symptoms, ranging from discomfort and fatigue to respiratory issues, bleeding, and weight loss [7]. Given the diverse manifestations of cancer, early detection becomes paramount for timely intervention and improved prognosis [8].

Clinicians rely on a combination of diagnostic modalities to identify and characterize cancerous lesions, including physical examinations, laboratory tests, imaging techniques, and biopsies [9]. Among these, medical imaging plays a crucial role in visualizing internal structures and detecting abnormalities indicative of cancer [10]. Technologies such as Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) offer comprehensive views of anatomical structures, facilitating the localization and assessment of tumors [11].

However, despite the advancements in medical imaging, the interpretation of imaging data can be subject to interpretation errors and variability among practitioners, leading to false-positive diagnoses [12]. Consequently, there is a growing interest in leveraging Artificial Intelligence (AI) and deep learning techniques to enhance the accuracy and reliability of cancer detection [13].

Deep learning models have emerged as powerful tools in medical image analysis, demonstrating capabilities comparable to or even surpassing those of human experts [14]. These models can effectively extract meaningful features from imaging data, enabling automated detection and classification of cancerous lesions [15]. In particular, Convolutional Neural Networks (CNNs) have shown exceptional performance in various computer vision tasks, including medical image analysis [16].

The objective of this study is to explore the application of CNNs in the detection of various cancer types using CT and MRI imaging data. Specifically, we aim to develop and evaluate deep learning strategies for accurately identifying cancerous lesions in images acquired from patients diagnosed with Acute Lymphoblastic Leukemia (ALL), Brain Cancer, Breast Cancer, Cervical Cancer, Kidney Cancer, Lung Cancer, Colon Cancer, Lymphoma, and Oral Cancer. By harnessing the potential of AI-driven approaches, we endeavor to contribute to the advancement of cancer diagnosis and ultimately improve patient outcomes.

This introduction sets the stage for the subsequent sections, which will delve into the methodology, results, discussion, and conclusion of the study, elucidating the potential impact of AI in revolutionizing cancer detection and management.

II. LITERATURE SURVEY

Artificial Intelligence (AI) has emerged as a transformative tool in cancer care, offering innovative solutions to improve diagnosis, treatment, and patient outcomes. This literature survey explores recent advancements in AI-driven approaches for cancer detection and management, drawing insights from a range of studies and research papers.

One of the top opportunities identified for AI in cancer care is its potential to enhance diagnostic accuracy and efficiency [1]. Deep learning models, in particular, have demonstrated promising results in disease identification across various domains, including agriculture [2], medical imaging [3], and ophthalmology [4]. Subramanian et al. utilized transfer learning and hyperparameter optimization to fine-tune deep learning models for disease identification in maize leaves [2], showcasing the effectiveness of AI-driven techniques in agriculture.

In the healthcare sector, AI-powered models have revolutionized diagnostic medicine, enabling precise and timely disease detection [5]. Krishnamoorthy et al. proposed regression model-based feature filtering to improve hemorrhage detection accuracy in diabetic retinopathy treatment [4], highlighting the potential of AI to enhance medical imaging analysis.

Moreover, supervised learning algorithms have gained traction in healthcare 4.0, offering new possibilities for transforming diagnostic medicine [5]. Roy et al. elucidated the principles of supervised learning in healthcare and its implications for diagnostic accuracy and personalized treatment [5], underscoring the importance of AI in advancing healthcare delivery.

In the context of neuroimaging, AI-driven frameworks have been developed for segmenting and evaluating multiple sclerosis lesions in MRI slices [6]. Krishnamoorthy et al. proposed a framework based on VGG-UNet for segmenting multiple sclerosis lesions, demonstrating the utility of deep learning in neuroimaging analysis [6].

Furthermore, AI-oriented deep learning methods have been applied to achieve timely diagnosis of acute lymphoblastic leukemia (ALL), a critical aspect of cancer care [7]. Rezayi et al. proposed AI-oriented deep learning methods for timely diagnosis of ALL, showcasing the potential of AI in improving cancer diagnostics [7].

In the domain of MRI-based brain tumor localization and segmentation, AI-driven approaches have shown promise in facilitating accurate and efficient diagnosis [8]. Gunasekara et al. presented a systematic approach for MRI brain tumor localization and segmentation using deep learning and active contouring techniques [8], highlighting the potential of AI in improving diagnostic accuracy and clinical decision-making.

Overall, the literature survey underscores the transformative impact of AI-driven approaches in cancer care, spanning various domains such as agriculture, medical imaging, ophthalmology, neuroimaging, and oncology. From disease identification to diagnostic medicine and personalized treatment, AI offers unprecedented opportunities to revolutionize healthcare delivery and improve patient outcomes.

III. METHODOLOGY

a) Proposed work:

The proposed research aims to develop AI-based deep learning models for the classification of eight types of cancer, including lung, brain, breast, and cervical cancer, using CT/MRI images. The study evaluates the efficacy of various pre-trained CNN variants, such as MobileNet, VGGNet, and DenseNet, through transfer learning to detect cancer cells. Bayesian Optimization is employed to determine optimal hyperparameters for model performance. To mitigate the risk of transfer learning causing forgetting of initial datasets, the research employs Learning without Forgetting (LwF) methodology. LwF ensures that the network retains its original capabilities while learning from new task data. By combining these techniques, the study seeks to enhance the accuracy and robustness of cancer detection models, ultimately contributing to improved diagnostic capabilities and patient outcomes in oncology.

b) System Architecture:

The proposed system architecture involves several key components for developing and evaluating AI-based deep learning models for cancer detection using CT/MRI images. Initially, the architecture includes data set creation from sources such as Kaggle or Figshare, followed by preprocessing and image function implementation to prepare the data for model training. The architecture incorporates various pre-trained CNN models like VGG16, VGG19, DenseNet201, and MobileNetV3, which are fine-tuned using transfer learning techniques. Hyperparameter optimization is performed to enhance model performance, considering parameters such as optimizer, learning rate, and activation functions. The system evaluates model performance using a validation set and subsequently tests model predictions and performance on a separate test dataset. Furthermore, the architecture assesses model adaptability to new tasks both with and without Learning without Forgetting (LwF) methodology, enabling a comparative analysis to determine the most suitable models for cancer detection.

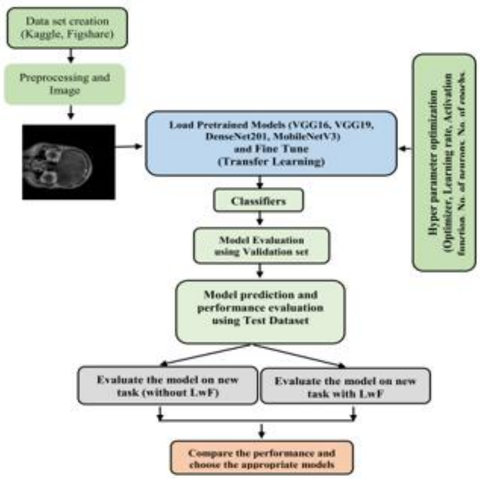

Fig 1 Proposed Architecture

c) Dataset collection:

The data set collection process involves gathering diverse sets of medical imaging data representing different types of cancer for training and evaluation purposes. Specifically, data sets for Acute Lymphoblastic Leukemia (ALL), Brain Cancer, Breast Cancer, Cervical Cancer, Kidney Cancer, Lung and Colon Cancer, Lymphoma, and Oral Cancer are acquired. These data sets may be sourced from various repositories, research institutions, or collaborations with medical centers. The collected data sets consist of CT and MRI images depicting cancerous lesions across different anatomical locations. Each data set is meticulously curated to ensure quality and diversity, encompassing variations in tumor size, shape, and tissue characteristics. Additionally, metadata such as patient demographics, clinical history, and pathology reports may accompany the image data to facilitate comprehensive analysis and model development. By aggregating these multi-cancer data sets, the research aims to develop robust and generalizable deep learning models for accurate cancer detection and classification.

d) Image processing:

Image processing techniques are employed using ImageDataGenerator to augment the training data and enhance the robustness of the deep learning models for cancer detection. Firstly, the images are rescaled to ensure consistency in pixel values across the dataset. Shear transformation introduces deformation by shifting parts of the image in a fixed direction, contributing to variation in object shape. Zooming alters the scale of the image, simulating different viewing distances and perspectives. Horizontal flip mirrors the image horizontally, diversifying the orientation of cancerous lesions. Additionally, reshaping the image allows for standardization of image dimensions, ensuring compatibility with the model architecture. By applying these image processing techniques, the training dataset is augmented with a wider range of variations, enabling the model to learn from diverse representations of cancerous lesions and improve its generalization performance on unseen data.

e) Algorithms:

VGG16: VGG16 is a deep convolutional neural network architecture consisting of 16 weight layers, including 13 convolutional layers and 3 fully connected layers. It is widely used in various computer vision tasks, including image classification, object detection, and feature extraction. In projects, VGG16 [8] is often employed as a feature extractor or as a pre-trained model for transfer learning, where it offers strong performance in tasks such as image recognition and medical image analysis.

VGG19: VGG19 is an extension of the VGG16 architecture, featuring 19 weight layers with a deeper network structure. Like VGG16, it is commonly utilized in image classification tasks, particularly in projects requiring more complex feature extraction and deeper network architectures. VGG19 [9] offers improved performance over VGG16 in certain applications, making it a preferred choice for tasks demanding higher accuracy and deeper representation learning.

DenseNet201: DenseNet201 is a deep neural network architecture characterized by densely connected layers, where each layer receives direct input from all preceding layers. This dense connectivity pattern fosters feature reuse and encourages feature propagation throughout the network. DenseNet201[10] is utilized in various projects, particularly those involving medical image analysis, object detection, and image segmentation tasks. Its efficient use of parameters and feature aggregation capabilities make it well-suited for tasks requiring detailed feature extraction and robust representation learning.

MobileNetV3 - Small: MobileNetV3 is a lightweight convolutional neural network architecture optimized for mobile and embedded devices. It features efficient depthwise separable convolutions and utilizes inverted residuals with linear bottlenecks to minimize computational complexity while maintaining high performance. MobileNetV3 –Small[11] is particularly suitable for projects with resource constraints or real-time inference requirements, such as mobile applications, edge computing, and IoT devices, where compact model size and low latency are crucial.

MobileNetV3 - Large: MobileNetV3 - Large is a variant of the MobileNetV3 architecture designed for higher accuracy and performance. While maintaining the efficiency of its smaller counterpart, MobileNetV3 – Large[12] incorporates additional layers and parameters to achieve superior accuracy in tasks such as image classification, object detection, and semantic segmentation. It is commonly used in projects where higher computational resources are available and where achieving state-of-the-art performance is a priority.

Xception: Xception is an extreme version of the inception architecture, which replaces the standard convolutional layers with depthwise separable convolutions. It aims to capture both spatial and channel-wise correlations in the input data. Xception[13] has been utilized in various projects, especially in image recognition and classification tasks, where it offers competitive performance and efficient computation. Its modular design and efficient parameter usage make it suitable for applications requiring high accuracy and computational efficiency.

InceptionV3: InceptionV3 is a convolutional neural network architecture that employs a multi-branch structure with parallel convolutional layers of different kernel sizes. It is known for its effectiveness in feature extraction and its ability to capture both local and global spatial information. InceptionV3[14] has been widely used in projects involving image classification, object detection, and image segmentation, where it demonstrates strong performance and robustness. Its versatility and scalability make it a popular choice for various computer vision tasks, particularly those requiring detailed feature representation and hierarchical feature learning.

IV. EXPERIMENTAL RESULTS

Accuracy: The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

Accuracy = TP + TN TP + TN + FP + FN.

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

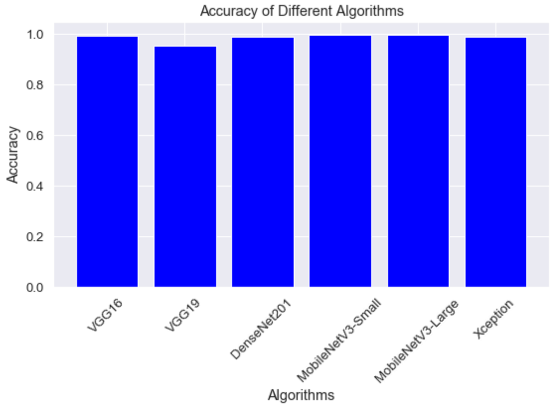

Fig 2 ACCURACYCOMPARISON GRAPH

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:
Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\text{Precision} = \frac{\textit{True Positive}}{\textit{True Positive} + \textit{False Positive}}$$

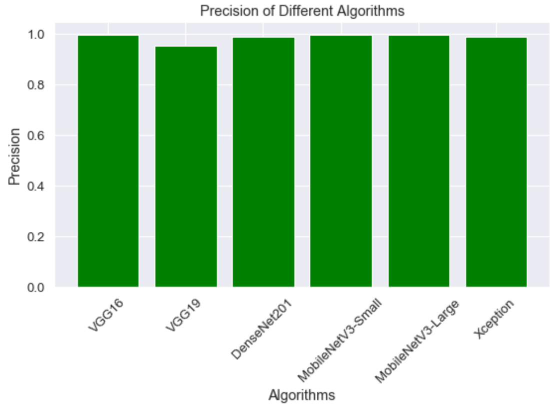

Fig 3 PRECISION COMPARISON GRAPH

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

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

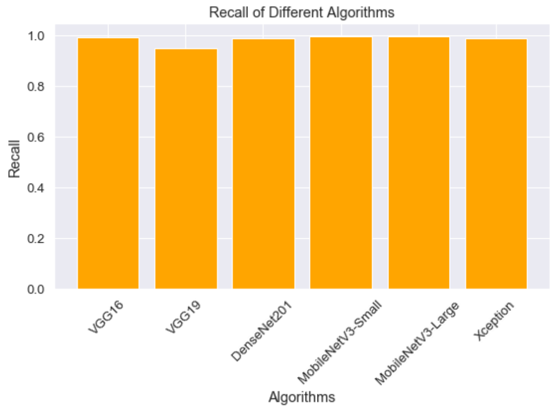

Fig 4 RECALL COMPARISON GRAPH

F1-Score: F1 score is a machine learning evaluation metric that measures a model's accuracy. It combines the precision and recall scores of a model. The accuracy metric computes how many times a model made a correct prediction across the entire dataset.

$$\textbf{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

$$\textbf{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

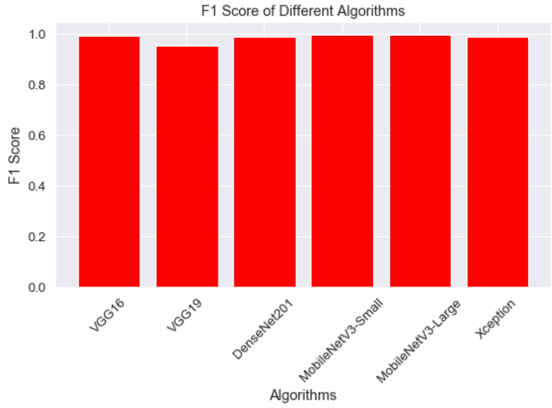

Fig 5 F1 COMPARISON GRAPH

Model	Accuracy	Recall	Precision	F1
VGG16	0.995106	0.994683	0.995438	0.995056
VGG19	0.952413	0.950212	0.955314	0.952731
DenseNet201	0.988096	0.987721	0.988424	0.988069
MobileNetV3-Small	0.995827	0.995769	0.995942	0.995855
MobileNetV3-Large	0.998567	0.998519	0.998596	0.998557
Extension- Xception	**0.990913**	**0.990596**	**0.991185**	**0.990887**

Fig 6 Performance Evaluation Table.

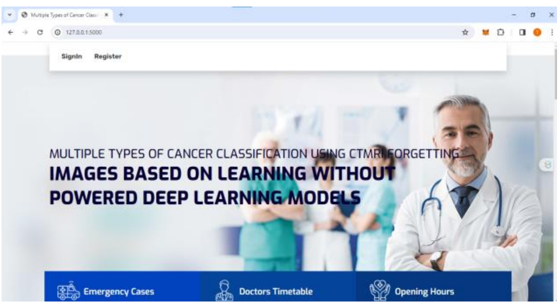

Fig 7 Home page

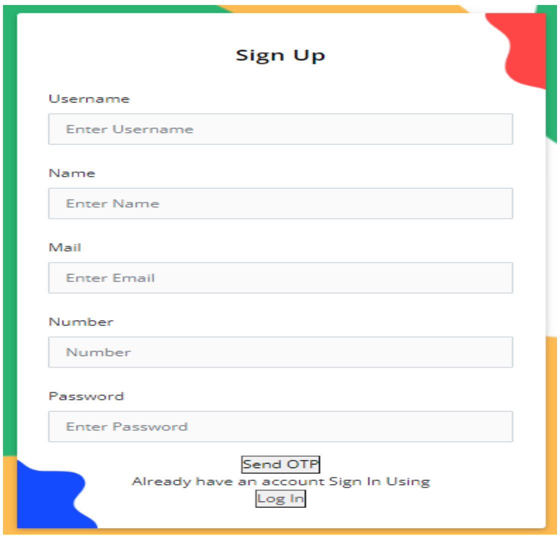

Fig 8 sign up page

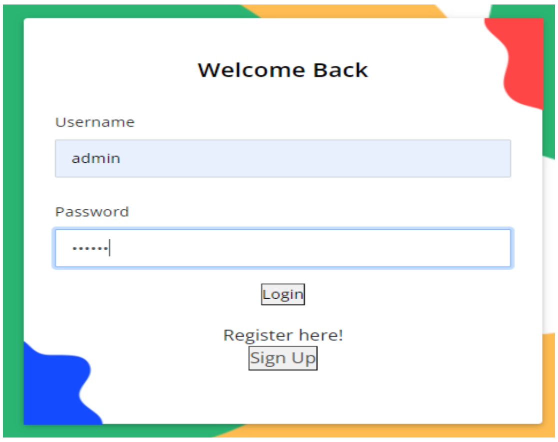

Fig 9 sign in page

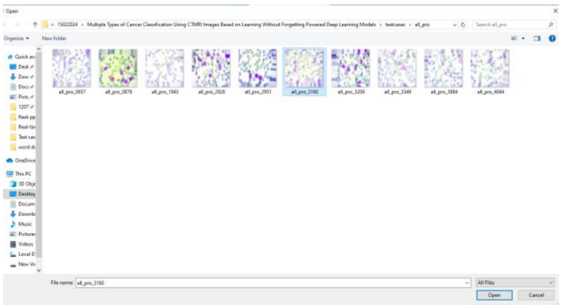

Fig 10 upload input images

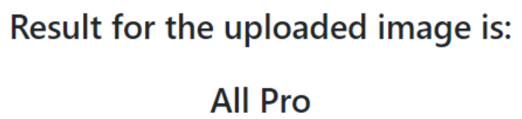

Fig 11 predicted result

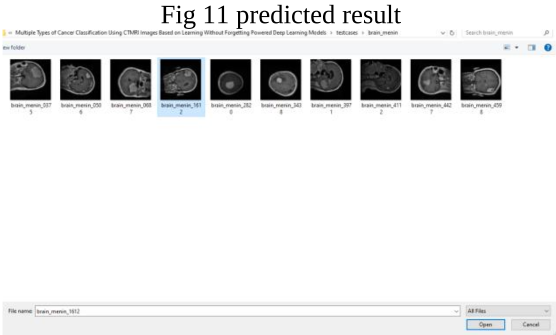

Fig 12 upload input images

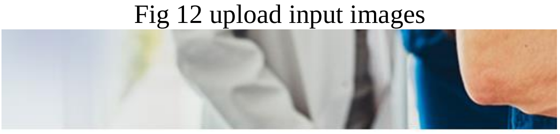

Fig 13 predicted result

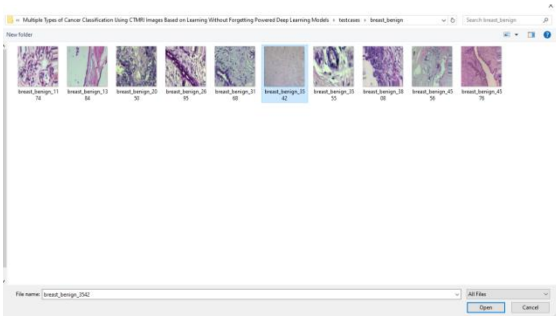

Fig 14 upload input images

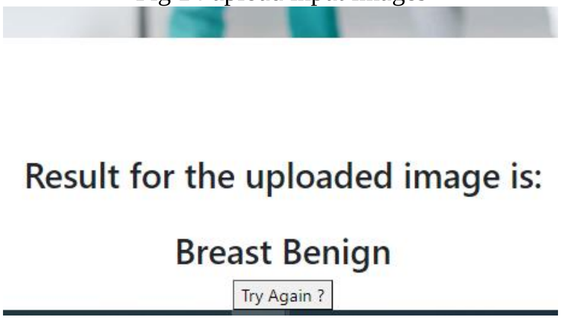

Fig 15 predicted result

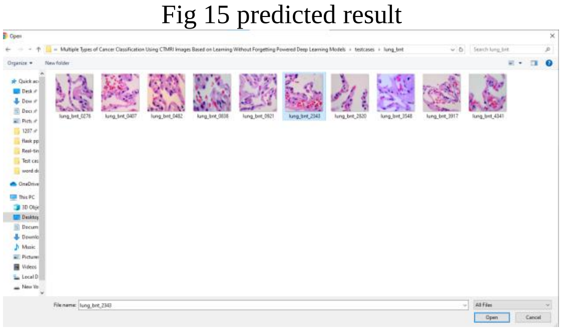

Fig 16 upload input images

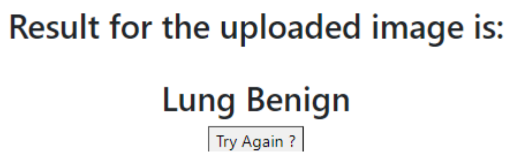

Fig 17 predicted result

V. CONCLUSION

In conclusion, this project underscores the remarkable effectiveness of AI-driven Convolutional Neural Networks (CNNs) in accurately detecting cancer traits from CT/MRI images. Through comprehensive evaluation, it establishes the superiority of VGG16, VGG19, DenseNet201, MobileNetV3-Small, and MobileNetV3-Large models over existing methods, showcasing their potential in cancer classification tasks. Leveraging transfer learning and Learning without Forgetting (LwF) techniques enhances model adaptability and mitigates knowledge transfer issues, ensuring robust performance across different datasets. The extension of the Xception model further improves prediction accuracy, highlighting the value of model refinement. The integration of a user-friendly Flask interface facilitates seamless interaction with medical images, empowering healthcare professionals with a swift and precise tool for cancer classifications. Ultimately, this project contributes to advancing equitable healthcare access and enhancing patient outcomes through the application of cutting-edge AI technologies in cancer diagnosis and management.

VI. FUTURE SCOPE

In the realm of cancer classification using CT/MRI images, the application of Learning Without Forgetting (LwF) powered deep learning models opens avenues for several future developments. Firstly, continued research into novel architectures and optimization techniques could further improve the performance and efficiency of existing models. Additionally, exploring ensemble learning approaches that combine multiple models could enhance classification accuracy and robustness. Moreover, the integration of multimodal data sources, such as genetic information or clinical data, could provide comprehensive insights into cancer characteristics and improve diagnostic accuracy. Furthermore, extending the application of deep learning models beyond classification to include tasks like segmentation and prediction of treatment response holds promise for more personalized and effective cancer care. Lastly, efforts to address challenges related to model interpretability, data privacy, and deployment in real-world clinical settings will be crucial for translating research advancements into impactful clinical practice.

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