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Multiple Types of Cancer Classification Using CT/MRI Images Based on Learning Without Forgetting Powered Deep Learning Models

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Abstract:

We propose AI, in particular, DL models, as a tool of automatically identifying This study examined a number of cancer types, including cervical, lung, breast, and brain cancer. VGG16, VGG19, DenseNet201, MobileNetV3 (small and large versions), Xception, and InceptionV3 are the CNNs that we are utilizing. Using the previously trained models (MobileNet, VGGNet, and DenseNet), we apply transfer learning to them. The best values for the model's hyperparameters are found via Bayesian optimization, which guarantees the model's efficacy. We use Learning without Forgetting (LwF), which preserves the original network, to solve any problems with ML. skills and enhances the ability of the network to classify new data sets. Our experiments indicate that our approach is more correct than others. The accuracy of MobileNet-V3 small on the Multi Cancer dataset was 86% accuracy. We are taking a peep at forecast approaches that rely on Xception and InceptionV3 to give it an additional boost. We are looking at achieving a minimum of 90 percent. We also suggest an extension to leverage the Flask framework to develop an intuitive front-end, which will make it easier for users to test the app after logging in. This study illustrates how AI-assisted early cancer detection could lead to better diagnosis and therapy.

"INDEX TERMS Cancer, convolutional neural network (CNN), pretrained models, Bayesian optimization,transfer learning, learning without forgetting, VGG16, VGG19, DenseNet, mobile net".

1. INTRODUCTION

Cancer is a complex illness, which has a great number of victims, and the development of inappropriate growth and reproduction of cells. Failure to treat, will render it fatal [1]. It ranks among the greatest issues of the health of the population, and it befalls individuals of all ages and regions. Recent information has shown that cancer is the leading cause of death in the world. This demonstrates that we must be capable of locating, identifying and treating cancer in a timely and efficient manner [2].

Cancer may be brought about by a combination of genetic factors and environmental factors that are many in number. Having high body mass index (BMI), smoking or taking alcohol, being near substances that are physically harmful such as ultraviolet (UV) radiation and ionizing radiation, are some of the behavioral characteristics that can significantly increase cancer risk among individuals [3]. Moreover, carcinogenesis can also be influenced by long-term inflammation, infectious agent and hormonal changes [4]. It is due to this that cancer can impact a huge number of various body organs and cells [5].

Some of the most frequent locations of cancer formation include lungs, mammary glands, cerebrum, colon, rectum, hepatic organ, stomach, integument, and prostate gland. Every type of cancer possesses its signs and symptoms. They may consist of pain and fatigue, difficulty in breathing, bleeding, and weight loss [7]. Given the elevated prevalence of cancer symptoms, early detection is of paramount importance. to allow the treatment to commence immediately and the prognosis could be improved [8].

To identify and characterize cancer spots, physicians apply a combination of the diagnostic tools, comprising physical examinations, analytical analyses, imaging modalities, and biopsies [9]. Medical imaging is essential for seeing interior structures. organs of the body and detection of cancer [10]. Such technologies as CT and MRI simplify the process since they provide us with detailed images of the structures of the body [11].

Nonetheless, despite the advancements in medical imaging, false-positive results may be provided by the error of interpreting imaging data and variations in the process of doctor interpretation [12]. Due to this reason, the application of AI and DL to improve the accuracy and reliability of cancer diagnosis is gaining popularity [13].

DL models have demonstrated human-like or better abilities when applied to medical images [14]. These models are able to extract significant elements of imaging data that allow sorting and identifying pictures of cancerous lesions automatic [15]. Specifically, CNNs have performed exceptionally well at a variety of many computer vision challenges, including the analysis of medical pictures [16].

The objective of the research work is to investigate how the CNNs may be applied to identify various forms of cancer using the CT and MRI scan data. To be more precise, we would like to design and experiment DL approaches to the accurate detection of photos showing malignant lesions in people having a diagnosis of ALL, brain, breast, cervical, kidney, lung, colon, lymphoma, or oral cancer. With AI's assistance, we can create new manners of operating things and, eventually, assist patients to improve due to the advancement of cancer detection.

This introduction provides the foundation of the following sections, where the methods of the study, results, and conclusions will be discussed and how AI is likely to impact a massive impact in altering the way we discover and treat cancer.

2. LITERATURE SURVEY

AI has become a highly significant resource in the sphere of cancer care, introducing new methods of assisting with the diagnosis, treatment, and patient outcomes. The literature review examines emerging AI-based approaches to identifying and treating cancer. It takes data based on numerous studies and research articles.

Among the most promising opportunities of AI in cancer treatment, one can mention the fact that it could assist in making the diagnosis more precise and faster [1]. Overall, DL models demonstrated highly positive results in disease detection in numerous areas of application, such as ophthalmology [4], medical imaging [3], and agriculture [2]. Subramanian and associates. applied hyperparameter optimization and transfer learning to enhance DL models to discover diseases in corn leaves [2]. It is one of the ways that AI-based approaches can be effective in agriculture.

AI-based models have transformed the entire landscape of medical medicine in healthcare, as they have allowed discovering diseases within a short time and in the most accurate way [5]. To simplify the process of detecting hemorrhages in diabetic retinopathy treatment, Krishnamoorthy et al. provided regression model-based filtering of the features [4]. This indicates that medical imaging analysis can be improved using AI.

In addition, supervised learning algorithms are gaining popularity in Healthcare 4.0, which offers fresh opportunities to revolutionize medical diagnosis [5]. Roy et al. talked about ML in the context of healthcare and what it implies to the quality of the diagnosis and individualized treatment [5]. This demonstrates the significance of AI in ensuring healthcare becomes better.

Neuroimaging instruments have been developed through AI to divide and examine various lesions of multiple sclerosis on MRI sections [6]. In the article by Krishnamoorthy et al., a VGG-UNet-based tool that was proposed on separation of multiple sclerosis lesions is presented, and it demonstrates the effectiveness of DL in neuroimaging [6].

In addition, the acute lymphoblastic leukemia (ALL) can be diagnosed in time, which is a significant aspect of cancer treatment, as well, and it has been ensured with the help of AI-based deep learning techniques [7]. According to Rezayi et al., the given AI-oriented DL techniques are aimed at rapid diagnosis of ALL, implying that AI can be used to make cancer testing more effective [7].

The AI-based approaches have been instrumental in assisting to ensure that brain tumor localization and segmentation are accurately diagnosed and in a short period of time based on MRI [8]. Gunasekara et al. demonstrated the DL and active contouring techniques to display a systematic form of locating and partitioning MRI brain tumours [8]. This article demonstrates the way AI can be used to make the diagnosis more precise and make clinical decision-making more effective.

In general, the literature review demonstrates that AI-based approaches revolutionized the manner in which we handle cancer and various other fields such as oncology, neuroimaging, ophthalmology, agriculture, and medical imaging. AI has been used in illness research, diagnosis, medication, and individual treatment. can entirely transform the nature of providing healthcare, and assist patients in a manner never existed before.

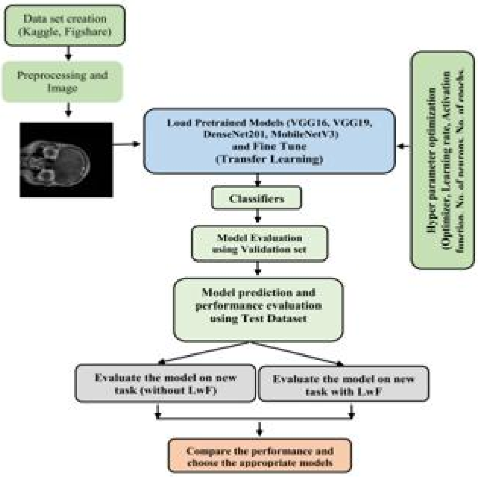
3. METHODLOGY

a) Proposed work:

The planned study's goal is to acquire CT and MRI images and create AI-driven DL frameworks that can differentiate between eight distinct cancer kinds, such as brain, lung, breast, and cervical cancer. The research employs ML to discover the extent to which the various types of pre-trained CNNs, such as MobileNet, VGGNet, and DenseNet, are capable of discovering cancer cells. The best hyperparameters of a model to work well are found using Bayesian Optimization. The research adopts the LwF approach to minimize the possibility of datasets forgetting due to the transfer learning. LwF ensures that the network retains its fundamentals skills since it learns new information concerning tasks. Combining the methods will enable the study to achieve more accurate and powerful cancer detection models. Eventually, it will enable the doctors to better perform cancer diagnosis and better patient outcomes.

b) System Architecture:

The proposed system design contains several significant components of creating and testing AI-based DL models to identify cancer in CT and MRI images. Firstly, it takes a data set of resources such as Kaggle or Figshare and performs preprocessing on the data after which it uses image functions to prepare the data to be trained on a model. Some of the CNN models that are already trained and are utilized in this design include VGG16, VGG19, DenseNet201, and MobileNetV3. Transfer learning makes these models more precise in this particular application. The hyper parameter optimization looks at optimizer, learning rate, activation functions, and other aspects in order to make models perform better. The system measures the execution of a model using a validation set. Then it checks or tests the predictions and performance of the model on a different set other than the validation set called a test dataset. It is also in the architecture that the capability of the model to adapt to new tasks is tested in the presence of the LwF approach and in the absence of it. This allows one to conduct a comparative study and identify the most appropriate models of finding cancer.



"Fig 1 Proposed Architecture"

c) Dataset collection:

In order to train and test the data gathering process, a variety of medical photos of different cancer types will be gathered. The data sets for ALL, brain, breast, cervical, kidney, lung and colon, lymphoma, and oral cancer in particular. These data sets are available through a variety of databases, research facilities, or partnerships with medical facilities. The gathered data sets include MRI and CT scans of malignant tumors in various body parts. Every data set is highly assembled to ensure that they are of high quality and that they are diverse; they consist of various types of shapes, sizes, and tissue characteristics of tumors. It is also useful in adding metadata to the image data to be analyzed and fully modeled. Some of the information that can be included in this metadata is the age, sex, and clinical background of the patient and pathology reports. The objective of the research in uniting These multi-cancer data sets are intended to produce strong and widely applicable DL that will find and classify cancer in an accurate fashion.

d) Image processing:

Image data generator is employed to supplement the training data by image processing techniques. This renders DL models on cancer detection more stable. Firstly, the images are rescaled such that the pixel values of the dataset are identical. Shear transformation is used to alter the form of an object by sliding various sections of the picture in a fixed direction. Once Zooming is applied, the size of the picture is changed allowing it to appear as though it has been captured at a new distance or a new angle. Horizontal flip transforms the horizontal position of the image and the cancerous lesions appear to be different. Reshaping the picture also ensures that the size of the pictures is the same size thus ensuring that the model design can handle the pictures. With such image processing algorithms, more types of examples have been included to the training dataset. This improves the model's ability to extrapolate to new data and enables it to learn using different forms of malignant tumors.

e) Algorithms:

VGG16: VGG16 is a DCNN, which consists of 16 convolutional and 3 weights that are totally connected. It can be used in a wide range of computer vision applications, including object identification, picture analysis, and feature detection. In transfer learning projects, the VGG16 [8], a feature extractor, is usually used as a pre-trained model. It works quite well for tasks like picture identification and medical image analysis.

VGG19: An update to VGG16 is called VGG19. It is deeper and has 19 layers. People typically use it for picture classification jobs, especially those that need for more elaborate networks and sophisticated feature extraction. structures, similarly to VGG16. In certain instances, VGG19 [9] is effective compared to VGG16. VGG19 is recommended in the job opportunities, which require greater accuracy and representation, and hence ML.

DenseNet201: DenseNet201 is a DNN model that has densely connected layers. All the layers receive the input of all the preceding levels. The fact that this pattern of connection is so dense means that reuse of network features and propagation of features is prevalent. DenseNet201 [10] is many times used in various projects, particularly the ones which require attention to medical images, seeking objects, and dividing images into pieces. It is efficient in terms of its parameter-use and feature-aggregation properties; hence, it is suitable to applications requiring robust representation-learning and elaborate feature-extraction.

MobileNetV3 - Small: an easy to use CNN architecture that is optimized to operate on hardware that is embedded and mobile. It features effective depthwise separable convolutions and inverted residuals with linear bottlenecks to guarantee that its calculations are straightforward yet effective. MobileNetV3-Small[11] can be used in projects that have limited resources or faster inference is required such as edge computing, IoT devices, mobile applications. These kind of projects require model size and delay to be short and small respectively.

MobileNetV3 - Large: MobileNetV3 -Large is an adaptation of MobileNetV3 architecture that is trained to be more precise and functional. MobileNetV3-Large[12] increases the number of layers and parameters of its smaller counterpart to enable it to be more precise in tasks including semantic segmentation, object detection, and image classification. People frequently use it in projects where additional computer power is accessible and the optimal results are valued.

Xception: Xception is a drastic variant of inception design. It employs depthwise separable convolutions as opposed to depthwise separable convolutions. It is aimed at identifying relationships, in the data it receives as input, both spatially and channel-wise. Many additional projects have made use of Xception [13], mostly in image recognition and categorization, due to its efficiency in the task as well as not being too long to compute. It is good to use in tasks that require a high precision and fast processing due to its modular shape and clever utilisation of its parameters.

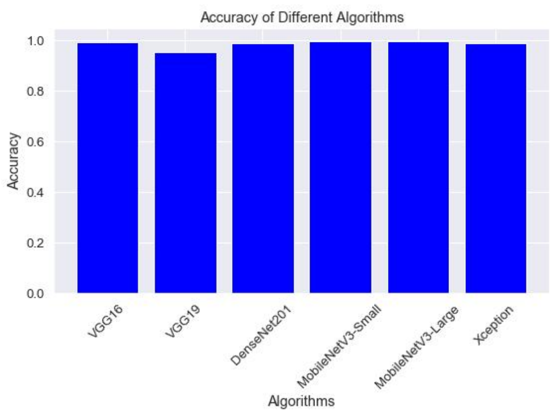
InceptionV3: CNN with several branches and parallel layers of different kernel-size convolution make up InceptionV3. It is recognized to be very good in extracting features and retrieving both local and world spatial information. It has been applied a lot in projects that involve picture segmentation, object detection, and image classification, which inceptionV3 demonstrates that it is a good and efficient procedure. It is an excellent tool on the tasks of most computer vision tasks since it can be adapted to a variety of tasks, and most computer vision tasks require describing a great number of details about features, and learning about features in a hierarchy.

4. EXPERIMENTAL RESULTS

Accuracy: A test's accuracy is determined by its capacity to distinguish between instances that are ill and those that are healthy. We should calculate the percentage of true positives and true negatives across all tested instances in order to gauge a test's accuracy. In mathematical notation, this would be written as

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

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

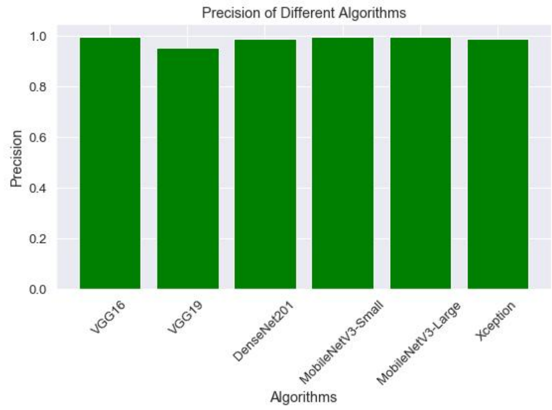


"Fig 2 ACCURACYCOMPARISON GRAPH"

Precision: Precision is used to measure the proportion of correctly identified examples or occurrences of the ones that have been identified to be positive. The procedure of determining the accuracy is:

"Precision = True positives/ (True positives + False positives) = TP/(TP + FP)"

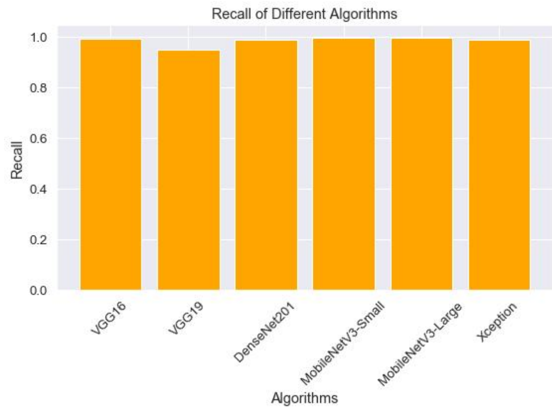
$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$



"Fig 3 PRECISION COMPARISON GRAPH"

Recall: Recall is a ML parameter which demonstrates the level of capacity of a model to recognize every suitable example of a particular class. It is the ratio of accurately forecasted positives to all positives that actually occurred. This provides the data regarding the degree of completeness of a model in terms of representation of the instances in a particular class.

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

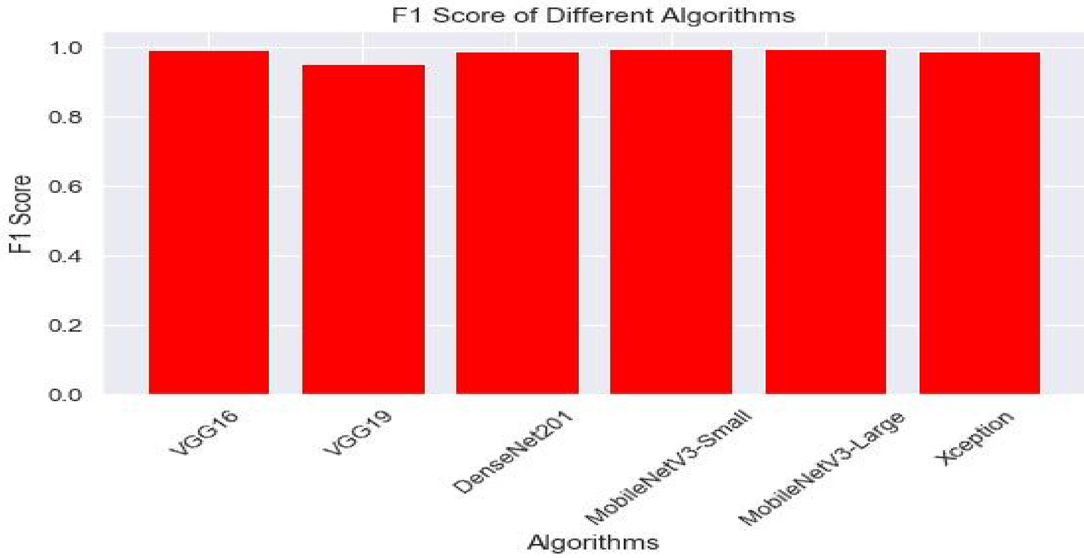


"Fig 4 RECALL COMPARISON GRAPH"

F1-Score: The F1 score is a way to measure how accurate an ML model is. It integrates a model's recall and accuracy scores. The accuracy metric will confirm how many of the model's predictions were accurate throughout the whole dataset.

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

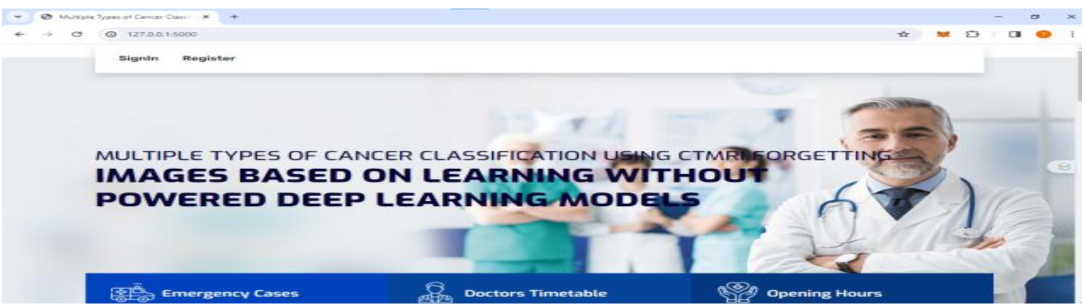
$$\textbf{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$



"Fig 5 F1 COMPARISON GRAPH"

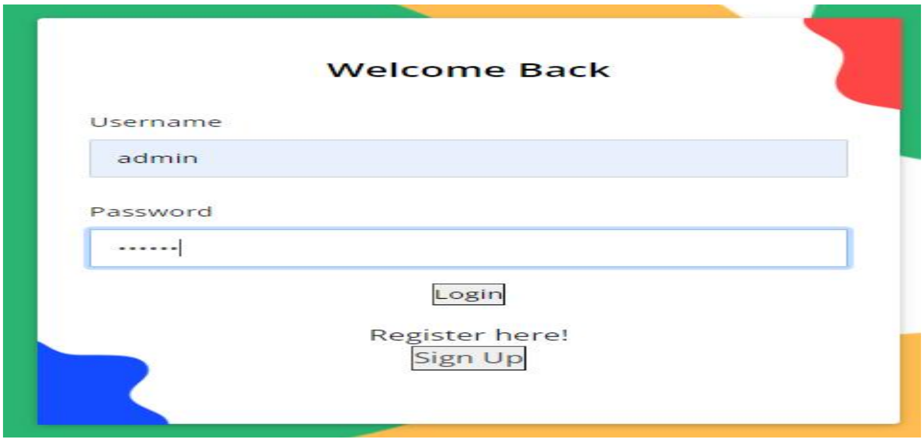
Model	Accuracy	Recall	Precision	F1
VGG16	0.995106	0.994683	0.995438	0.995056
VGG19	0.952413	0.950212	0.955314	0.952731
DenseNet201	0.988096	0.987721	0.988424	0.988069
MobileNetV3-Small	0.995827	0.995769	0.995942	0.995855
MobileNetV3-Large	0.998567	0.998519	0.998596	0.998557
Extension- Xception	**0.990913**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

"Fig 6 Performance Evaluation Table".



"Fig 7 Home page"

“Fig 8 sign up page”



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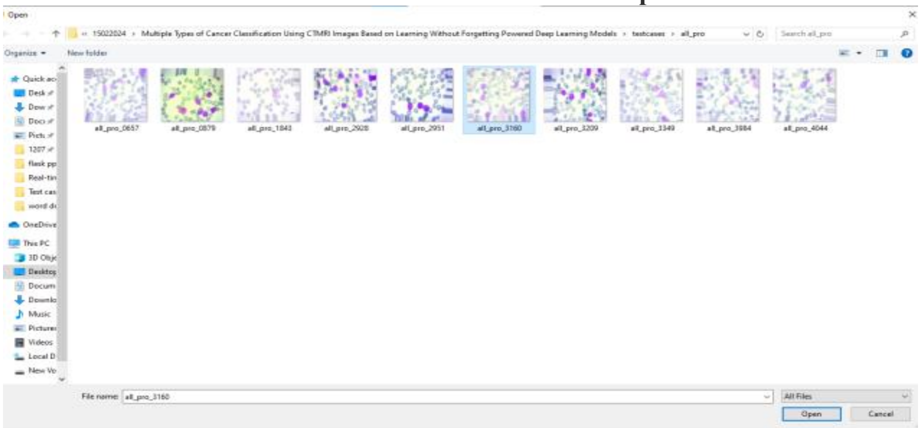
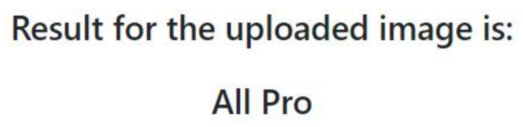
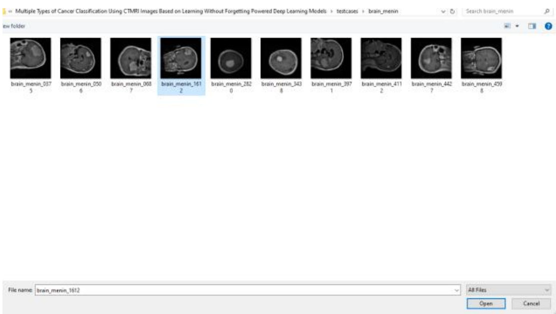


“Fig 10 upload input images”



“Fig 11 predicted result”



“Fig 12 upload input images”

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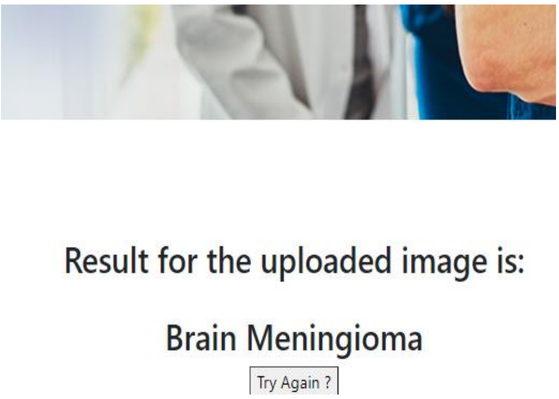
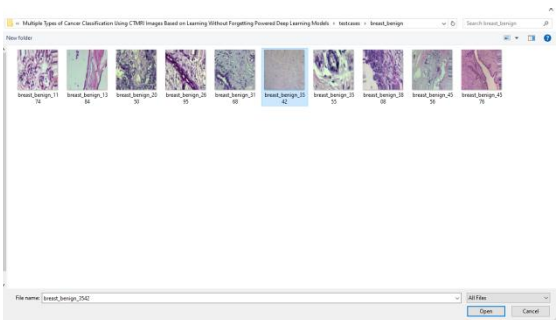


“Fig 13 predicted result”



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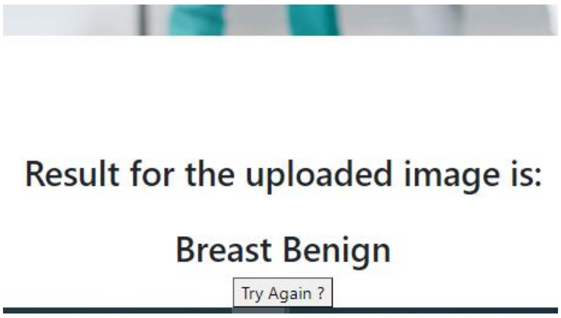
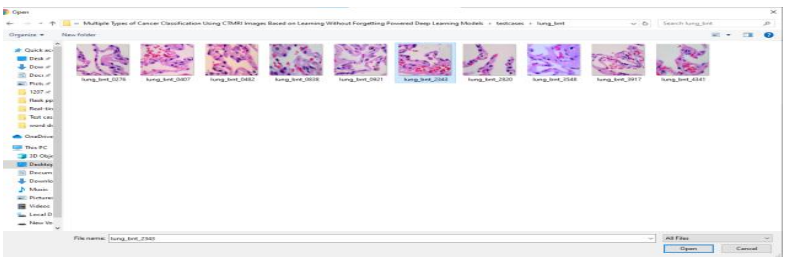
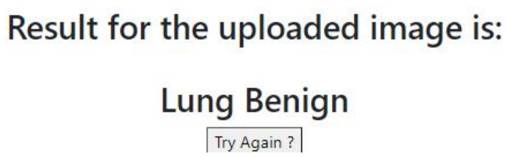


“Fig 15 predicted result”



"Fig 16 upload input images"



"Fig 17 predicted result"

5. CONCLUSION

Lastly, the current project demonstrates the effectiveness of AI-based CNN in the correct recognition of cancerous features in CT and MRI images. Using a wide scope of tests, it demonstrates that the VGG16, VGG19, DenseNet201, MobileNetV3-Small and MobileNetV3-Large models are superior to the earlier techniques, which proves that they may be effective in placing cancer cases into one of the categories. Application of transfer learning and LwF renders models more adjustable and aids in transfer of knowledge that ensures that they perform on various datasets. The inclusion of Xception model further enhances predictions, which demonstrates that it is useful to enhance models. Working with the medical images is easier due to the addition of a Flask interface which is easy to use. This will provide healthcare workers with a fast and precise method when categorizing cancers. Lastly, with the adoption of the most recent AI technologies to enhance the process of diagnosis and treatment of cancer, this project will assist in enhancing patient outcomes and ensuring that all people have access to the necessary healthcare.

6. FUTURE SCOPE

DL models based on LwF allow making a plethora of different kinds of progress when it comes to the classification of cancer based on the CT/MRI pictures. First, the exploration of further building designs and optimization mechanisms may aid the improvement of the performance of the existing models and make them more efficient and effective. It might be also useful to consider ensemble learning that would combine a number of models. It might also be important to synthesize the various forms of data such as genetic or clinical data to have a better understanding of the cancer and ensure that the diagnoses are made properly. Moreover, it might be beneficial to apply deep learning models to processes beyond classification and apply them to such tasks as segmentation and prediction of treatment response to make cancer care more personalized and efficient. And lastly, the model interpretability, data security, and practicality in clinical settings environments are also concerns that need to be addressed before research can impact clinical practice in a real way.

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