Multiple Types of Cancer Classification Using CTMRI Images Based on Learning without Forgetting Powered Deep Learning Models

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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.

Keywords - *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 disease characterized by abnormal cellular growth and uncontrolled proliferation, posing a major global health challenge and ranking among the leading causes of death worldwide [1,2]. Its development is influenced by a combination of genetic predispositions and environmental factors. Behavioral risks such as high body mass index (BMI), tobacco and alcohol use, as well as exposure to carcinogens like ultraviolet (UV) and ionizing radiation, play critical roles in carcinogenesis [3]. Additional contributors include chronic inflammation, infectious agents, and hormonal imbalances [4].

Cancer manifests across multiple organs, including the lungs, breasts, brain, colon, liver, stomach, skin, and prostate, with symptoms ranging from fatigue and weight loss to bleeding and respiratory issues [5–7]. Early detection is essential to improve prognosis, making accurate diagnostic techniques indispensable [8]. Clinicians employ physical examinations, laboratory tests, imaging modalities, and biopsies, with Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) being crucial for visualizing tumors [9–11]. However, interpretation errors and diagnostic variability remain challenges, often leading to false positives [12].

II. RELATED WORK

Artificial Intelligence (AI) has emerged as a transformative tool in cancer care, offering innovative solutions to enhance diagnosis, treatment, and patient outcomes. This literature survey reviews recent AI-driven advancements in cancer detection and management.

One major opportunity for AI in cancer care is its potential to improve diagnostic accuracy and efficiency [1]. Deep learning models have shown remarkable performance across diverse domains, including agriculture [2], medical imaging [3], and ophthalmology [4]. For instance, Subramanian et al. applied transfer learning and hyperparameter optimization to fine-tune deep learning models for maize leaf disease identification, illustrating the broader effectiveness of AI techniques [2].

In healthcare, AI-powered models have significantly impacted diagnostic medicine by enabling precise and timely disease detection [5]. Krishnamoorthy et al. proposed regression model-based feature filtering to enhance hemorrhage detection in diabetic retinopathy, highlighting AI's utility in medical imaging [4]. Supervised learning algorithms have also gained traction, offering new avenues for improving diagnostic accuracy and personalized treatment [5]. Roy et al. elaborated on supervised learning principles in healthcare, emphasizing their role in transforming diagnostic practices [5].

In neuroimaging, AI frameworks have been developed for segmentation and evaluation of multiple sclerosis lesions in MRI slices. Krishnamoorthy et al. employed a VGG-UNet-based framework for lesion segmentation, demonstrating deep learning's effectiveness in neuroimaging analysis [6]. Similarly, AI-oriented methods have been applied to achieve timely diagnosis of acute lymphoblastic leukemia (ALL), a crucial component of cancer care. Rezayi et al. highlighted deep learning strategies for ALL detection, emphasizing AI's role in early cancer diagnostics [7].

Moreover, MRI-based brain tumor localization and segmentation have benefited from AI-driven approaches. Gunasekara et al. proposed a systematic method using deep learning combined with active contouring techniques, facilitating accurate tumor identification and enhancing clinical decision-making [8].

III. PROPOSED METHODOLOGY

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.

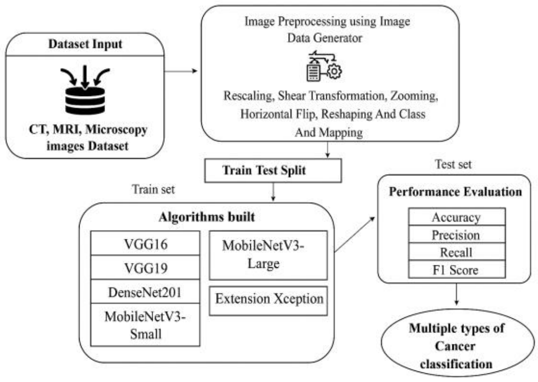


Fig.1 Proposed Architecture

The system architecture for AI-based cancer detection involves dataset creation and preprocessing from sources like Kaggle, followed by implementing pre-trained CNN models (VGG16, VGG19, DenseNet201, MobileNetV3) fine-tuned via transfer learning. Hyperparameter optimization, validation, and testing ensure performance evaluation. Additionally, Learning without Forgetting (LwF) is applied to assess model adaptability and determine the most effective approach for cancer detection.

A) Dataset Collection:

The dataset collection involves acquiring diverse medical imaging data for multiple cancers, including ALL, brain, breast, cervical, kidney, lung, colon, lymphoma, and oral cancers, from repositories, research institutions, or medical collaborations. The curated CT and MRI images capture variations in tumor size, shape, and tissue characteristics. Accompanying metadata, such as patient demographics, clinical history, and pathology reports, supports comprehensive analysis. These multi-cancer datasets enable the development of robust, generalizable deep learning models for accurate cancer detection and classification.

B) 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.

C) Algorithms:

VGG16: VGG16 is a deep CNN with 16 weight layers (13 convolutional, 3 fully connected), widely used for image classification, object detection, and feature extraction. It excels as a pre-trained model for transfer learning in medical and general image analysis [8].

VGG19: VGG19 extends VGG16 with 19 weight layers, providing a deeper network for complex feature extraction. It offers improved accuracy and representation learning, making it suitable for tasks demanding high precision in image recognition and medical imaging [9].

DenseNet201: DenseNet201 features densely connected layers, allowing each layer to receive inputs from all previous layers. This promotes feature reuse and robust representation, making it ideal for medical image analysis, segmentation, and object detection tasks [10].

MobileNetV3 – Small: MobileNetV3–Small is a lightweight CNN optimized for mobile and edge devices, using depthwise separable convolutions and inverted residuals. It achieves efficient real-time inference with low latency while maintaining high accuracy [11].

MobileNetV3 – Large: MobileNetV3–Large builds on the small variant with additional layers and parameters, achieving higher accuracy. It is suitable for tasks requiring state-of-the-art performance where sufficient computational resources are available [12].

Xception: Xception replaces standard convolutions with depthwise separable convolutions to capture spatial and channel-wise correlations. Its efficient design enables high-accuracy image recognition and classification with reduced computational cost [13].

IV. RESULTS AND DISCUSSION

Accuracy: A test's accuracy is its capacity to distinguish patient from healthy cases. To measure test accuracy, calculate the fraction of true positive and true negative in all evaluated cases. Mathematically, this is:

$$Accuracy = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{FP} + \mathrm{TN} + \mathrm{FN}} (1)$$

Precision: Precision measures the percentage of positive cases or samples accurately classified. Precision is calculated using the formula:

$$Precision = \frac{\text{True Positive}}{\text{True Positive } + \text{False Positive}} (2)$$

Recall: Machine learning recall evaluates a model's capacity to recognise all relevant instances of a class. It shows a model's completeness in capturing instances of a class by comparing accurately predicted positive observations to total positives.

$$Recall = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} (3)$$

F1-Score: Machine learning model accuracy is measured by F1 score. Combining model precision and recall scores. The accuracy statistic measures how often a model predicted correctly throughout the dataset.

$$F1\ Score = 2 * \frac{Recall \text{ X } Precision}{Recall + Precision} * 100 (4)$$

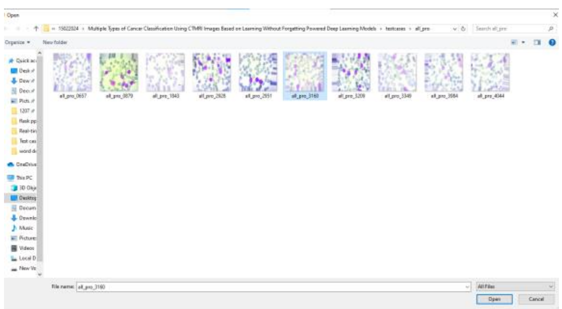


Fig.2 Upload Input Image

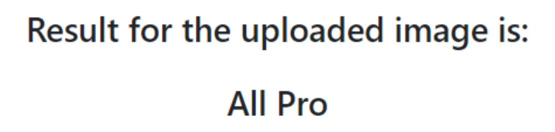


Fig.3 Predicted Results

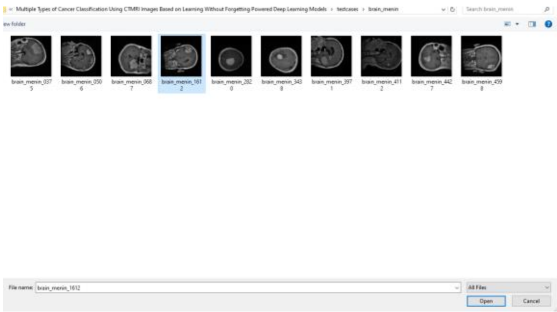


Fig.4 Upload Input Image

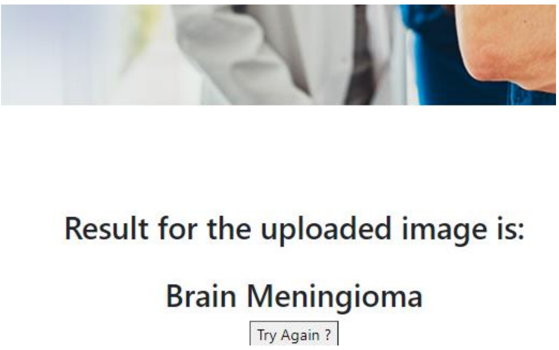


Fig.5 Predicted Results

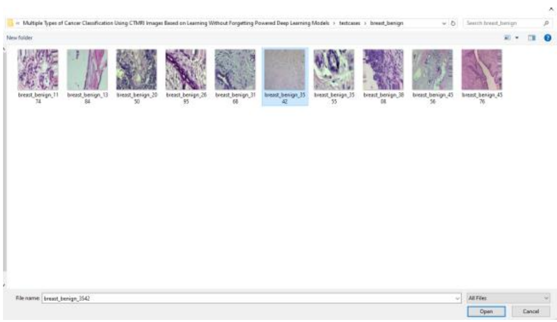


Fig.6 Upload Input Image

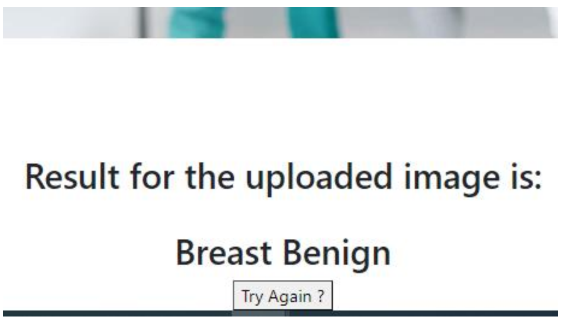
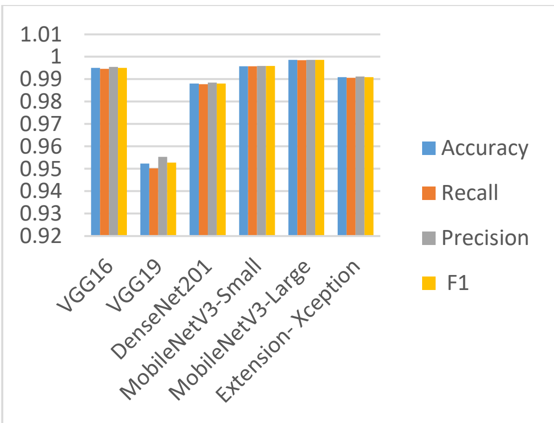


Fig.7 Predicted Results

Table (1) evaluate the performance metrics—Accuracy, precision, recall and F1-score —for each algorithm. The Xception model consistently outperforms compared to all other algorithms. The tables also offer a comparative analysis of the metrics for the other algorithms

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
MobileNet V3-Small	0.995827	0.995769	0.995942	0.995855
MobileNet V3-Large	0.998567	0.998519	0.998596	0.998557
Extension-Xception	0.990913	0.990596	0.991185	0.990887

Graph.1 Comparison Graphs



Accuracy in blue, precision is represented in grey, recall in orange and F1-Score in yellow Graph (1). In comparison to the other models, the Xception model shows superior performance across all metrics, achieving the highest values. The graphs above visually illustrate these findings.

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.

Future developments in cancer classification using LwF-based deep learning models include optimizing architectures for improved performance, employing ensemble and multimodal approaches integrating genetic or clinical data, and extending applications to segmentation and treatment response prediction. Addressing model interpretability, data privacy, and real-world deployment will be key to translating these advancements into effective and personalized clinical cancer care.

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