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Multicancer Detection using CNNs

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ABSTRACT: The increasing global burden of cancer demands timely and accurate diagnostic tools to improve patient survival rates and support clinical decision-making. This research introduces an intelligent deep learning framework designed to automatically detect multiple cancer types—including brain, breast, lung, cervical, colon, kidney, oral, and lymphoma—through analysis of medical images. The system is built using Convolutional Neural Networks (CNNs), with a focus on VGG and EfficientNet architectures, which are known for their robust performance in image classification tasks. A diverse set of cancer-related medical images is collected and pre-processed through normalization, resizing, and augmentation techniques to enhance the dataset's quality and variability. Both CNN models are trained on this data and evaluated using performance indicators such as accuracy, recall, and precision. The results reveal that the VGG architecture consistently achieves higher accuracy and computational stability compared to EfficientNet across various cancer classes. Based on this performance, the VGG model is deployed in a web-based interface, developed using the Flask framework, which allows users to upload images and receive real-time predictions. The system aims to assist medical professionals by reducing the time and potential human errors involved in manual diagnosis. Overall, the study demonstrates that CNN-based models, particularly those using the VGG architecture, have strong potential to support early detection of cancers and contribute to better healthcare outcomes.

Keywords: Cancer detection, Deep learning, Convolutional Neural Network, VGG, Medical imaging.

1. Introduction

Cancer remains one of the foremost challenges in global healthcare, contributing to millions of deaths each year. Early diagnosis plays a crucial role in improving treatment outcomes, yet traditional diagnostic methods often rely on manual inspection of medical images by specialists, which can be time-consuming, prone to human error, and inconsistent across practitioners. Recent advances in artificial intelligence have opened new avenues for improving diagnostic accuracy and efficiency, particularly using deep learning models. Among these, Convolutional Neural Networks (CNNs) have shown exceptional performance in medical image classification tasks, enabling automated systems that can learn complex features directly from image data.

This research addresses the pressing need for an automated, reliable, and accurate diagnostic system capable of identifying multiple types of cancer. While several studies have applied CNNs to individual cancer types—such as breast, brain, or lung—limited work has been done on designing a single unified system that can detect multiple cancers from diverse medical images. To tackle this gap, the proposed study explores the use of VGG and EfficientNet architectures, both known for their robust feature extraction capabilities and high accuracy in visual recognition tasks. The authors have implemented a multi-stage approach that includes image preprocessing, model training, evaluation, and deployment via a web interface, aiming to support clinicians in real-time decision-making.

The core objective of this research is to develop a deep learning-based platform that can efficiently classify various cancer types and deliver results through an accessible interface. In doing so, the study contributes to the growing field of AI-powered healthcare tools by offering a scalable, accurate, and user-friendly solution for early cancer detection. Prior work, such as that by Kumar et al. (2024) and Alabdulqader et al. (2024), has shown the potential of CNNs in healthcare; this project builds on those foundations to advance multi-cancer diagnosis.

2. Recent Works

In recent years, deep learning has significantly advanced the field of medical image analysis, particularly in cancer detection. Convolutional Neural Networks (CNNs) have been widely used for their ability to automatically extract and learn hierarchical features from complex image data. Several studies have validated the effectiveness of CNNs in identifying specific cancer types. For example, breast cancer has been successfully classified using mammographic images, while brain tumours and lung cancer have been detected using MRI and CT scans, respectively.

The architecture at the core of this study is VGGNet, introduced by Simonyan and Zisserman. VGG is known for its uniform structure, utilizing small (3x3) convolutional filters stacked in depth. This design not only simplifies implementation but also supports transfer learning, allowing the model to adapt effectively to new medical imaging datasets. Its simplicity and high accuracy have made it a preferred choice for many medical classification tasks.

In contrast, EfficientNet uses a compound scaling method to balance network depth, width, and resolution. Although it is designed to be more computationally efficient, our study focuses on evaluating both architectures in the context of multi-cancer detection to determine which provides the best trade-off between performance and speed.

Complementing these neural models, previous research such as that by Kumar et al. [1] emphasized the importance of automation in cancer diagnostics, using advanced CNN variants for image classification. Similarly, Alabdulqader et al. [2] proposed a lightweight, resource-efficient technique combining Local Binary Pattern (LBP) features with transfer learning to support low-power diagnostic tools.

Building upon these approaches, our study aims to refine and unify existing methodologies by applying them to a broad, multi-cancer classification task. The modifications include customized preprocessing steps for diverse cancer images and comparative evaluation of both CNN models to assess their real-world application in medical diagnostics.

3. Proposed Work Explanation

The development of this multi-cancer detection system is grounded in the theoretical strengths of deep learning, particularly the layered architecture of Convolutional Neural Networks (CNNs), which excel at recognizing patterns in image data. Rather than revisiting basic concepts, this section focuses on how the theoretical properties of two specific architectures—VGG and EfficientNet—were leveraged to address the challenges of multi-class cancer classification.

The VGG model, with its depth and uniform structure, enables the extraction of detailed features through consecutive convolution and pooling layers. This structure proves especially useful in identifying subtle variations in medical images associated with different cancer types. On the other hand, EfficientNet is built around a compound scaling technique, which balances the depth, width, and resolution of the network. While it is known for optimizing accuracy and efficiency simultaneously, our work evaluates its real-world reliability across multiple cancer datasets.

To ensure the models are trained effectively, image preprocessing is applied, including resizing, normalization, and augmentation. These steps enhance the model's ability to generalize across varied datasets. The system architecture incorporates a classification model, followed by output generation and result display through a user-friendly interface.

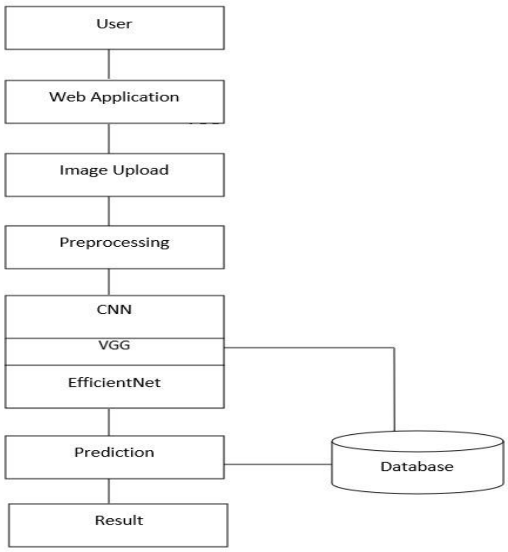


Figure 1: *Proposed block diagram*

3.1 Mathematical Expressions and Symbols

In the case of multi-cancer detection with Convolutional Neural Networks (CNNs), mathematical equations give an idea about how input medical images get transformed and processed to generate useful diagnostic features. One of the major operations in CNNs is the convolution operation, formulated mathematically as: The general form of the Fourier series used to represent a periodic function f ( ) f(x) is:

$$S(i,j) = (I * K)(i,j) = \sum_{m}\sum_{n} I(i+m, j+n) \cdot K(m,n)$$

where I is the input image, K is the kernel, and $S(i, j)$ is the feature map.

After convolution, a non-linear activation like ReLU is applied:

$$\text{ReLU}(x) = \max(0, x)$$

For classification into multiple cancers, CNNs use the categorical cross-entropy loss:

$$\mathcal{L}(y, \hat{y}) = -\sum_{c=1}^{C} y_c \log(\hat{y}_c)$$

Finally, model weights are updated using gradient descent:

$$W \leftarrow W - \eta \frac{\partial \mathcal{L}}{\partial W}$$

These mathematical steps allow CNNs to learn and detect different cancer types from medical images.

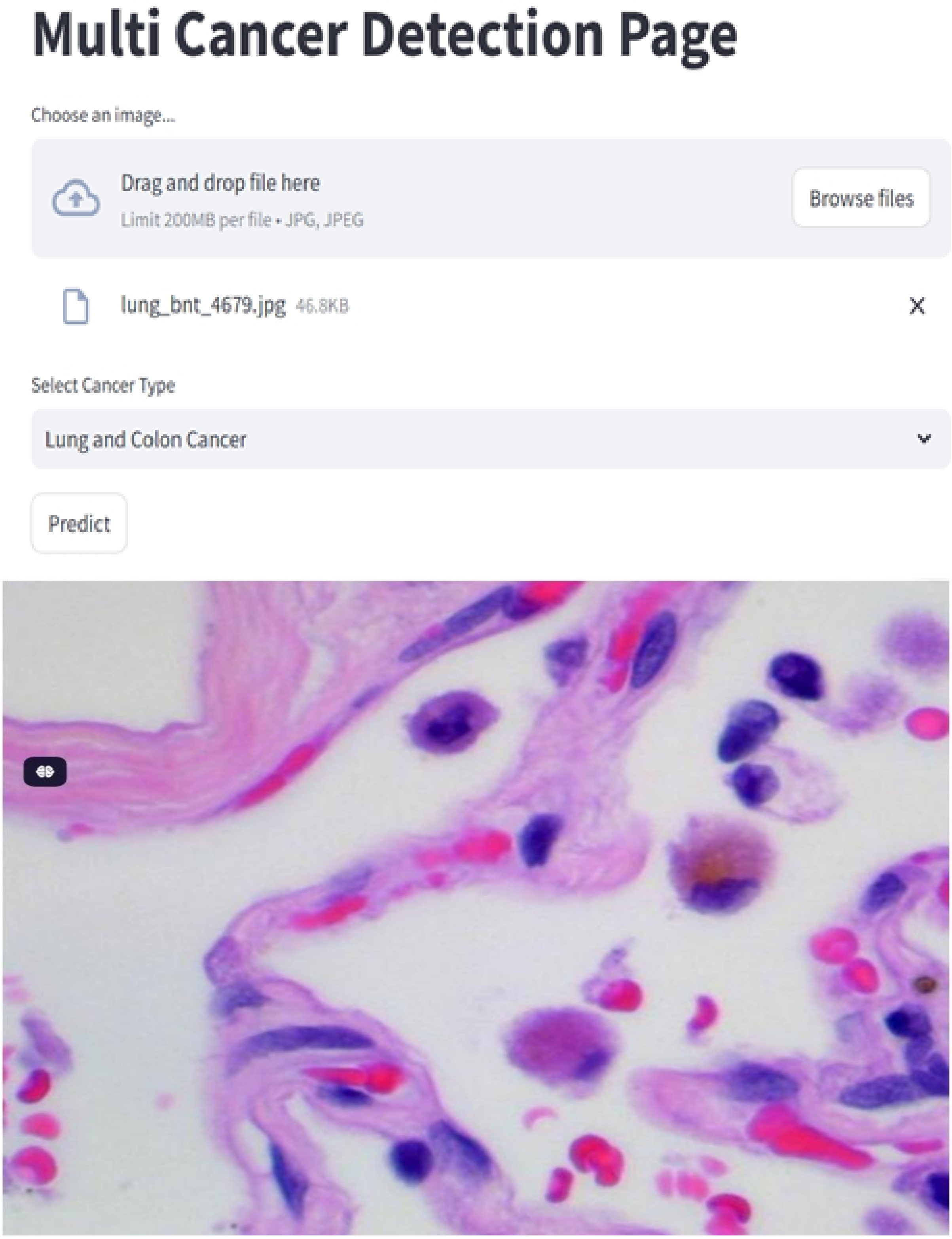
4. Results and Discussion

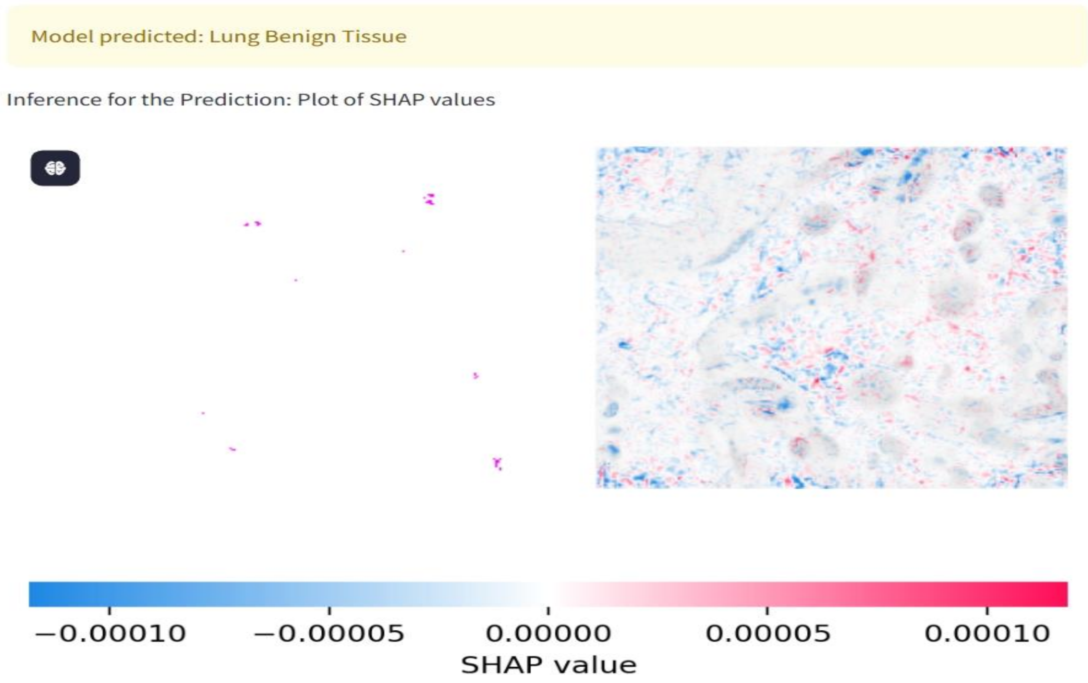
The multi-cancer classification system was successfully developed and deployed as a web-based application, enabling users to upload medical images and receive real-time diagnostic predictions. The performance of the system was evaluated based on key metrics including accuracy, precision, recall, and computational efficiency. Among the two CNN architectures tested, the VGG model consistently outperformed EfficientNet across most datasets, delivering more stable and accurate results in the classification of cancer types such as breast, brain, and lung.

This outcome highlights the advantage of VGG's deeper and more uniform architecture, which proves effective in capturing complex visual features that are critical in distinguishing between different cancer classes. Although EfficientNet offers computational benefits due to its compact design, its performance in terms of classification accuracy was slightly less reliable, particularly when dealing with imbalanced datasets or subtle image variations.

The deployed web application, built using Flask, serves as a practical tool for healthcare professionals by simplifying the diagnostic process. It minimizes manual effort, reduces the potential for human error, and delivers consistent results regardless of user experience level. The interface is intuitive, allowing for easy navigation and immediate access to predictions and visual feedback.

Compared to recent studies such as those by Kumar et al. (2024), which focused on single cancer type detection using CNNs, our work expands the scope by introducing a unified system capable of handling multiple cancers with comparable or improved accuracy. The study by Alabdulqader et al. (2024) emphasized resource efficiency, particularly for mobile devices, but lacked the high-level accuracy seen in VGG-based implementations. By balancing accuracy, usability, and real-world applicability, our project offers a novel contribution to the growing field of AI-assisted cancer diagnosis.





4.1 Preparation of Figures and Tables

All figures and tables used in this paper are integrated at appropriate locations within the text to ensure smooth flow and understanding of the content. Visuals such as system architecture diagrams and classification result snapshots have been included at the exact points in the discussion where they are most relevant, helping readers to directly relate the explanation to the visuals. Each figure and table is clearly labelled with a sequential number and a concise, descriptive title that reflects its content.

For example, Figure 1 illustrates the proposed system architecture used in the multi-cancer detection model, and this is referenced explicitly in the corresponding explanation within the Proposed Work section. Any tabulated results or visual elements are similarly referenced and discussed in the Results and Discussion section to ensure they are not isolated or unexplained.

Following best practices, none of the figures or tables are submitted separately or appended at the end of the document. This approach improves readability and allows reviewers and readers to grasp the context and significance of each visual element without needing to scroll or search. Care has been taken to maintain consistency in formatting and clarity in presentation to meet publication standards.

4.2 Formatting Tables

Table should be prepare using table tool within the Microsoft word and cited consecutively in the text. Every table must have a descriptive title and if numerical measurements are given, the units should be included in the column heading. Formatting requirement has been summarized in the Table 1.

Table 1: *Summary of formatting requirement for submitting paper in this journal.*

Layout	**Size**	**Margin (Normal)**	Header	Footer	
Single column	A4 (8.27” X 11.69”)	Top=1” Bottom=1” Left=1” Right=1”	Do not add anything in the header	So not add anything in the footer	
Font	**Article Title**	**Headings**	**Subheadings**	**Reference list**	**Text**

	Times New Roman, 16 pt, Bold, centred	Times New Roman, 12 pt, Bold, Left aligned	Times New Roman, 12 pt, Bold, Left aligned	Times New Roman, 10 pt, Justified	Times New Roman, 12 pt, Bold, Left aligned
Line Spacing	1.15	1.15	1.15	1.15	1.15
Page number	We will format and assign page numbers				

5. Conclusions

This study effectively designed a multi-cancer detection system using deep learning that can detect multiple forms of cancer, such as breast, brain, lung, kidney, colon, cervical, lymphoma, and oral cancer, from medical images. Using Convolutional Neural Networks, namely the VGG and EfficientNet architectures, the system showed consistent performance in classifying intricate visual information. After rigorous training and evaluation, the VGG-based model emerged as the more accurate and stable option for multi-class cancer diagnosis. Its consistent performance across diverse datasets makes it a suitable choice for real-world applications where diagnostic accuracy is critical. The project not only focused on developing an efficient model but also emphasized accessibility through the deployment of a user-friendly web interface. This interface enables medical images to be uploaded by healthcare professionals and receive real-time classification results, making the system usable and available for clinical setting integration. Perhaps the most significant contribution of the work is its potential to aid medical specialists by decreasing the effort and time consumed in manual diagnosis and guaranteeing objectivity and consistency. In spite of its encouraging findings, the study has some limitations, such as dependence on pre-existing datasets, which may not always represent current clinical situations. Additionally, the performance of the model could differ if subjected to images from novel or unseen machines with varying resolutions or image features. Future developments can involve using more varied datasets, making the system more adaptable, and broadening the classification to cover more types of cancer. Integration with hospital databases and application of continuous learning methods would further enhance the performance and applicability of the system over time. Overall, the project shows that CNN-based architectures, particularly VGG, have a lot of potential in aiding early cancer detection and can be crucial in improving the speed and accuracy of medical diagnosis when integrated with affordable digital platforms.

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