Journal of Harbin Engineering University
ISSN: 1006-7043

Vol 45 No. 10
October 2024

Multi-Organ Disease Detection With Enhanced Deep Learning Algorithms

[1] Anupama Potti, [2] Sushma V, [3] G Vidyu Latha, Ch Aruna Reddy, B Nirmala

[1] Assistant Professor,
Sree Dattha Institute of Engineering and Science, Hyderabad, Telangana state.
[2]Assistant Professor, ISE Department, Nitte Meenakshi Institute of Technology, Bangalore.
[3]Assistant Professor
Sree Dattha Institute of Engineering and Science, Hyderabad, Telangana state.
[4]Assistant Professor,
Sree Dattha Institute of Engineering And Science, Hyderabad, Telangana state.
[5]Holy Mary Institute Of Technology And Science, Keesara,Bogaram

Abstract
The project leverages deep learning techniques to develop a robust and efficient system capable of detecting diseases across multiple human organs. The increasing availability of medical imaging data and advancements in deep learning have made it possible to create models that can analyze complex patterns in medical data and assist healthcare professionals in early and accurate diagnosis. This project focuses on utilizing convolutional neural networks (CNNs) to analyze medical images such as X-rays, MRIs, or CT scans and classify diseases affecting different organs, including the heart, lungs, ovaries, and kidneys. By training on a diverse dataset, the model aims to identify early signs of disease, improving patient outcomes through timely intervention. The system's performance will be evaluated using key metrics such as accuracy, precision, recall, and F1-score, ensuring that it meets clinical standards. This project has the potential to streamline diagnostic processes, reduce human error, and enhance the decision-making process in medical practice.
Keywords: Organ disease, Machine Learning, Deep Learning EfficientNet, VGG19

I INTRODUCTION

The rapid advancement in medical technology has significantly transformed healthcare, with early disease detection playing a critical role in improving patient outcomes. Diseases affecting multiple organs such as the heart, lungs, liver, and kidneys are leading causes of morbidity and mortality worldwide. Timely and accurate diagnosis remains a challenge due to the complexity and diversity of medical data. This project, titled "Multi-Organ Disease Detection," utilizes deep learning, specifically convolutional neural networks (CNNs), to analyze medical images and identify diseases across various organs. Deep learning models excel at recognizing intricate patterns in data, making them ideal for medical diagnostics. By training the model on a large dataset of annotated medical images, the system aims to assist healthcare professionals by providing reliable disease predictions. The implementation of this system not only improves diagnostic accuracy but also reduces the time required for analysis. Ultimately, the project strives to enhance clinical decision-making and facilitate more effective treatment strategies through early disease detection.

II. STATE OF THE ART

Deep learning, a subset of artificial intelligence, has revolutionized various fields, including healthcare. At the core of deep learning are artificial neural networks, specifically Convolutional Neural Networks (CNNs), which have demonstrated remarkable success in image-based tasks such as classification, segmentation, and detection. In medical diagnosis, CNNs are particularly valuable due to their ability to analyze large-scale medical imaging data, such as X-rays, MRIs, CT scans, and histopathological images. The deep layers of CNNs automatically learn complex hierarchical features from raw images, making them highly effective at identifying subtle patterns that might be missed by human experts. This technology enables early and accurate detection of diseases, offering promise in improving patient outcomes through timely intervention.

Current Advances and Research in Multi-Organ Disease Detection

Several research studies have demonstrated the effectiveness of deep learning models in diagnosing diseases in various organs, each focusing on different datasets and methods to improve accuracy and efficiency. Some of the significant contributions include:

1) **Lung Disease Detection**:
Lung diseases, such as pneumonia, tuberculosis, and COVID-19, have been widely studied using deep learning techniques. Researchers have used chest X-rays and CT scans as primary datasets to train CNNs for disease classification. A notable study by Rajpurkar et al. (2017) introduced the "CheXNet" model, a 121-layer CNN that achieved human-level performance in detecting pneumonia from chest X-rays. The model was trained on the publicly available ChestX-ray14 dataset and outperformed radiologists in sensitivity and accuracy. Similar models have been adapted to detect other lung diseases, with CNNs consistently delivering accurate results.

2) **Cardiac Disease Detection**:
Cardiovascular diseases are a leading cause of death globally, and accurate early diagnosis is critical. Deep learning models have been applied to electrocardiogram (ECG) data and cardiac MRI images to identify conditions such as arrhythmia, heart failure, and myocardial infarction. For example, Hannun et al. (2019) developed a deep learning algorithm that achieved high accuracy in detecting arrhythmias using ECG signals. Another research by Tan et al. (2020) focused on CNN-based segmentation of the heart chambers from MRI images, which improved diagnostic precision for various cardiac conditions.

3) **Kidney Disease Detection**:
Kidney disease, particularly chronic kidney disease (CKD), is often diagnosed late, which complicates treatment. Deep learning techniques have been applied to ultrasound and CT imaging for the detection and classification of kidney stones, tumors, and cysts. In 2019, a research team led by Barash et al. proposed a CNN-based model that achieved excellent accuracy in detecting kidney tumors from CT images. Their findings showed that CNN models could be used as a reliable tool to assist radiologists in diagnosing kidney-related diseases early, improving patient prognosis.

4) **Multi-Organ Disease Detection**:
Recent studies have explored the application of deep learning models for multi-organ disease detection. These models are trained on multi-modal datasets, including a combination of X-rays, CT, and MRI scans, to identify diseases affecting multiple organs simultaneously. One example is the work by Irvin et al. (2019), who developed "CheXpert," a large-scale deep learning model for automated disease classification from chest X-rays. This model not only focused on lung diseases but also aimed at detecting conditions affecting other organs, such as heart failure and pleural effusion, marking a step toward multi-organ diagnostics. Similarly, researchers have been working on developing multi-task learning models that can simultaneously detect diseases in the lungs, liver, and kidneys by leveraging shared features from medical imaging data.

Challenges and Opportunities

Despite significant progress, challenges remain in developing and deploying deep learning models for multi-organ disease detection. A major hurdle is the limited availability of large, annotated datasets across multiple organs, which is essential for training robust and generalizable models. Furthermore, ensuring the interpretability and explainability of deep learning models is critical in gaining clinical trust and acceptance. Current research is increasingly focused on addressing these challenges by incorporating multi-modal data, such as integrating imaging data with patient demographics and lab results, and by using advanced techniques like attention mechanisms to improve model interpretability.

Nevertheless, deep learning has already proven its value in medical diagnostics, and with ongoing research and development, it holds great potential to become an integral tool in clinical settings. As the field continues to advance, models capable of detecting diseases in multiple organs with high accuracy and reliability will be key in transforming healthcare practices and improving patient outcomes.

III. THE PROPOSED METHOD

Problem statement

Developing a web-based application system using deep learning to detect multiple organs diseases. In this project we are providing a healthcare system which helps people to check the reports from hospitals. Also, the AI based approach using multiple deep learning algorithms, including EfficientNet, DenseNet, and VGG19 for disease detection can make the disease detection easy and helpful.

The main objectives of the proposed system are as follows:

1. **Multi-Organ Disease Detection**: Develop a system capable of detecting diseases in multiple organs, including the lungs, heart, ovaries, and kidneys, using medical images such as X-rays, CT scans, and MRIs.
2. **High Accuracy:** Achieve a high level of diagnostic accuracy through the use of deep learning models, ensuring that predictions are reliable and meet clinical standards.
3. **Data-Driven Insights**: Provide meaningful insights by training the model on a diverse dataset that reflects a wide range of medical conditions and patient demographics.
4. **Real-Time Processing**: Implement a system that performs real-time or near-real-time analysis of medical images, delivering quick results to assist in urgent medical scenarios.
5. **Scalability and Flexibility**: Build a scalable system that can be extended to include new organs and diseases over time, making it adaptable to the ever-evolving landscape of medical diagnosis.

The proposed system for "Multi-Organ Disease Detection" aims to create an automated, intelligent framework using deep learning techniques to detect diseases affecting multiple human organs. By leveraging the power of Convolutional Neural Networks (CNNs) and large-scale medical imaging data, this system seeks to improve the accuracy and efficiency of diagnosis for conditions affecting the lungs, heart, liver, and kidneys, among others. The system is designed to assist healthcare professionals by providing rapid, reliable disease predictions, helping in early detection and improving treatment outcomes. The integration of this deep learning system into healthcare workflows has the potential to reduce the diagnostic burden on radiologists, lower human error, and accelerate the decision-making process. The architecture of the project is as follows.

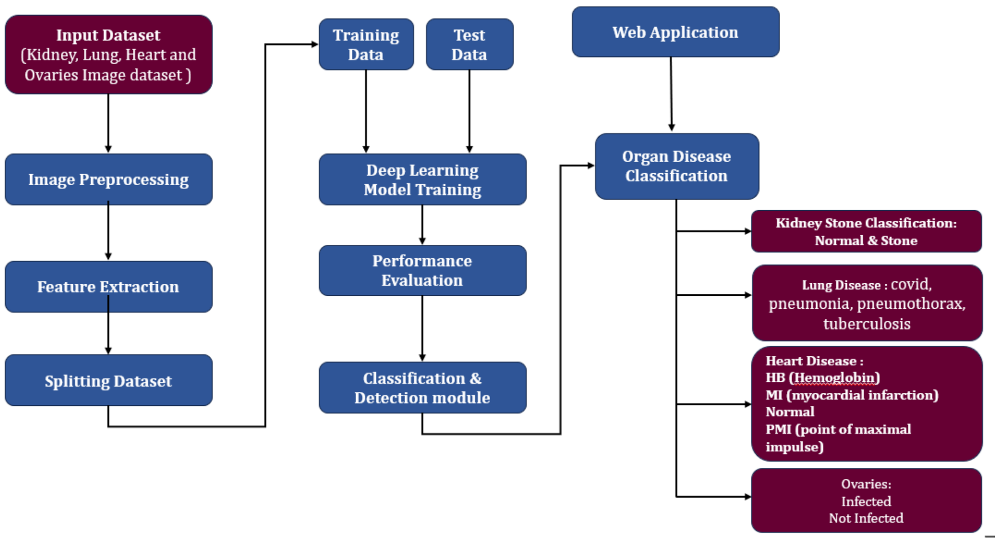


Figure 1: Architecture Diagram

Data Collection: The first step in building the proposed system is to gather a comprehensive dataset of medical images related to various organs. This will include X-rays, CT scans, MRIs, and ultrasound images from publicly available datasets such as ChestX-ray14, LIDC-IDRI (for lung cancer), and other specialized datasets for liver, heart, and kidney conditions. The dataset must be diverse, representing different age groups, genders, and disease states, ensuring the model can generalize across a wide population. Additional clinical metadata, such as patient history and symptoms, may also be included to enhance prediction accuracy.

Figure 2: Sample Dataset

Data Preprocessing:

Medical images often come with noise, irregularities, or varying resolutions that can affect the performance of the deep learning model. Therefore, the preprocessing step is crucial for preparing the data. This includes:

- **Image Resizing and Normalization**: Standardize the size and pixel values of the images so that they can be fed into the CNN model uniformly.
- **Noise Reduction**: Apply techniques such as Gaussian filtering or bilateral filtering to remove noise and enhance image quality.
- **Data Augmentation**: Increase the diversity of the dataset through techniques such as rotation, flipping, zooming, and contrast adjustment. This helps the model become more robust to variations in the input data.
- **Segmentation (if needed)**: In some cases, the system may require segmentation of specific organs (e.g., liver, heart) from the surrounding tissues to focus the model's attention on the region of interest.

Model Development:

The core of the proposed system is the deep learning model, specifically a Convolutional Neural Network (CNN), designed to analyze preprocessed medical images. Several architectures, such as ResNet, VGG, or DenseNet, may be employed depending on the complexity and requirements of the system. The model will be trained to classify diseases across different organs by learning the hierarchical patterns in the images. To enhance multi-organ detection, a multi-task learning approach may be implemented, where a single model is trained to perform disease classification across various organs simultaneously.

Training and Validation

The system will undergo extensive training on the collected dataset using labeled data. During training, the dataset will be split into training, validation, and test sets to ensure the model's performance is generalized and not overfitted. The training process will utilize optimization techniques like Adam or RMSProp to minimize the loss function, and performance will be evaluated using metrics such as accuracy, precision, recall, and F1-score.

Disease Classification and Prediction

Once trained, the CNN will be capable of predicting diseases from new, unseen medical images. For each input image, the system will output a classification label indicating the presence or absence of specific diseases in various organs. The predictions will be accompanied by confidence scores to help clinicians assess the reliability of the model's output.

Practical Implementations

- **Importing Packages:** Import the required libraries for the project. Here, we require Numpy, Tensorflow, keras, OpenCV and so on
- **Upload the Model (.*keras* File):** In this project, we have VGG19 ,EfficientNet and DenseNet Model. The performance is recorded and will be shown to users in the results page of the web application. Also, each algorithm model is saved and can be chosen by users for the prediction in the production of web application.
- **Function:**

a. **Upload the Image:** In the web application, users can upload an image of scans like MRI, CT etc.
b. **Read the Image:** Here, we are using NumPy to convert the image to array for the processing.
c. **Get Predictions:** Get prediction for the uploaded image as an array.
d. **Result:** Display result of the prediction as disease detected or not. If detected which category it belongs to.

Algorithms

VGG19:

VGG19 is a variant of the VGG (Visual Geometry Group) deep convolutional neural network, introduced by the researchers at Oxford University. It was designed to improve upon the performance of earlier convolutional networks by using a deep architecture composed of 19 layers. VGG19 is widely recognized for its simplicity and effectiveness, achieving high accuracy in image classification tasks, particularly in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC). The model is known for its uniform structure, using only small 3x3 convolution filters throughout the network.

Architecture:

The architecture of VGG19 consists of 19 layers, including 16 convolutional layers and 3 fully connected layers. It follows a simple design pattern where convolutional layers are stacked in increasing depth, followed by max-pooling layers for downsampling, and finally fully connected layers for classification. The network begins with a 224x224 pixel input image and ends with a softmax layer that provides class probabilities. VGG19 uses a consistent filter size of 3x3, and the depth of the network increases gradually as the network progresses, doubling the number of feature maps after each max-pooling layer.

- Convolutional Layers: 16 convolutional layers with 3x3 filters, organized into blocks.
- Pooling Layers: Max-pooling layers follow every two or three convolutional layers, reducing the spatial dimensions by half.
- Fully Connected Layers: Three fully connected layers are used at the end, with the final output being a softmax layer for classification.

Weight Layers:

VGG19 is composed of over 143 million parameters, a large proportion of which come from the fully connected layers. The weights are initialized using techniques such as Xavier initialization, which ensures that the weights are scaled correctly for optimal gradient flow. The convolutional layers use pre-trained weights, typically from the ImageNet dataset, to reduce the training time and improve the model's performance for transfer learning tasks.

The weight layers can be broken down as follows:

- **Convolutional Layers**: These layers are responsible for feature extraction from the input images. The weights are learned through backpropagation during training.
- **Fully Connected Layers**: These layers contain a large portion of the weights and are responsible for mapping the high-level features extracted by the convolutional layers to the final output class.

Input Specifications:

VGG19 expects an input image of fixed size 224x224 pixels with three channels (RGB). Before feeding into the network, the input image is resized and then normalized by subtracting the mean pixel values computed from the ImageNet dataset.

- **Input Dimensions**: (224x224x3)
- **Preprocessing**: Normalize by subtracting the ImageNet mean [R: 123.68, G: 116.779, B: 103.939] for each pixel channel.

Unique Characteristics:

- **Depth**: VGG19 is deeper than its predecessor models like AlexNet, making it capable of capturing more complex features from the input data.
- **Small Filters (3x3)**: VGG19 uses small 3x3 filters throughout, which allows it to capture fine-grained details while keeping the number of parameters manageable.
- **Uniform Design**: The simplicity and uniformity of the VGG19 architecture make it easy to implement and modify, while still achieving high accuracy.

Filter Sizes:

VGG19 consistently uses 3x3 convolutional filters across all convolutional layers. This small filter size is effective for capturing local spatial relationships and ensures that each layer only focuses on a small portion of the image. Despite the small filter size, the depth of the network allows it to capture complex hierarchical features. Additionally, the max-pooling layers use a 2x2 filter with a stride of 2 for downsampling.

- **Convolutional Layer Filter Size:** 3x3
- **Pooling Layer Filter Size:** 2x2 with stride 2

Fully Connected Layers

The final stage of the VGG19 network consists of three fully connected (FC) layers:

1. **FC1**: The first fully connected layer contains 4096 neurons and takes the flattened output from the last convolutional layer as input.
2. **FC2**: The second fully connected layer also contains 4096 neurons and applies a nonlinear activation function (ReLU).
3. **FC3**: The third and final layer has 1000 neurons, which correspond to the 1000 output classes in the ImageNet dataset. This layer uses a softmax activation function to output class probabilities.

- **Number of Neurons in FC Layers**: 4096 (FC1), 4096 (FC2), 1000 (FC3)
- **Activation Function**: ReLU for FC1 and FC2, Softmax for FC3

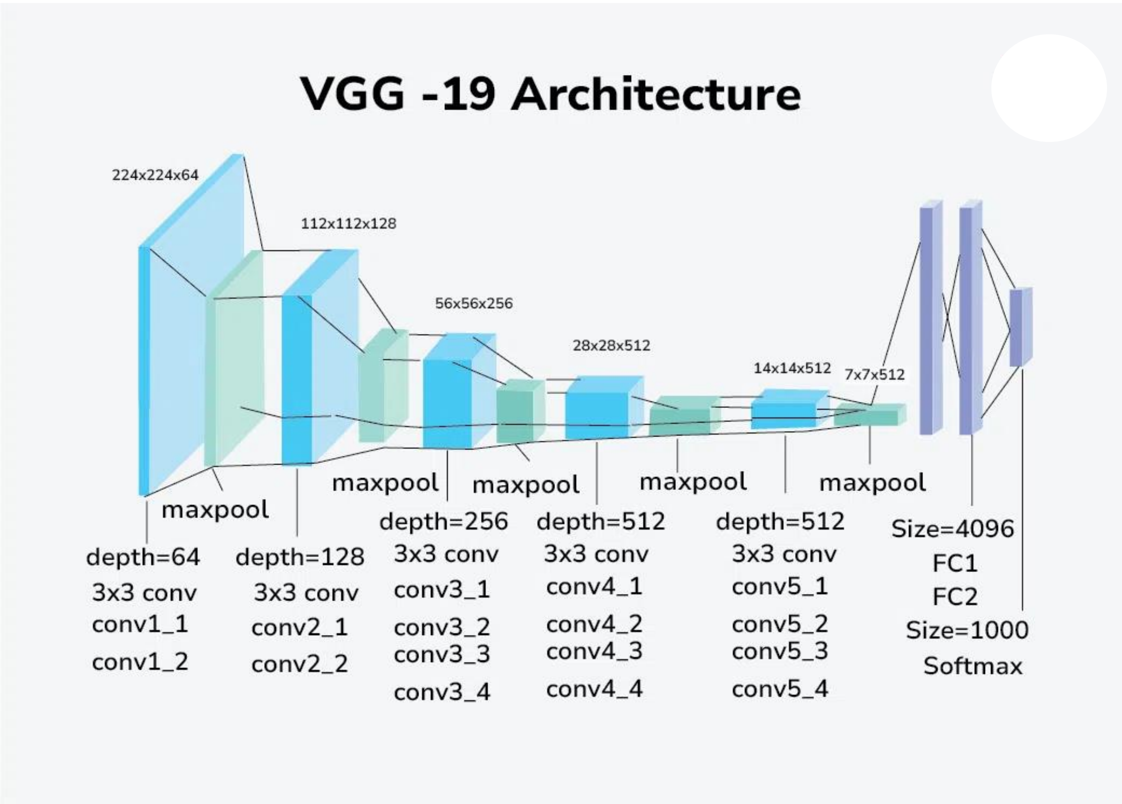


Figure 3: VGG19 Architecture

Iv. Experimental Results

The experiment resulted in the development of a Flask-based web application designed to perform organ disease detection using deep learning models. The system was trained on three state-of-the-art algorithms—EfficientNet, DenseNet, and

VGG19—each of which was fine-tuned for different organs. The models were specifically trained to classify diseases or identify the healthy state of four key organs, providing a multi-organ disease detection platform.

Model Training and Selection

Each model was trained on a labelled dataset containing images of four organs, with each image categorized as either healthy or exhibiting specific diseases. The three models—EfficientNet, DenseNet, and VGG19—were employed because of their efficiency in image classification tasks:

- **EfficientNet** was used for its scalability and balance between accuracy and model size.
- **DenseNet** was selected for its ability to promote feature reuse, leading to a more efficient learning process.
- **VGG19** was chosen due to its deep yet straightforward architecture, known for high performance in image classification tasks.

The models were trained separately for each organ with different classification objectives, such as identifying common diseases and healthy states, resulting in a highly specialized detection system.

Flask App Functionality

The Flask app allows users to interactively choose the model and the organ image to be scanned. The application flow is as follows:

1. **Input Image**: Users upload an image of the organ to be scanned (e.g., liver, lungs).
2. **Model and Organ Selection**: Users then select which model to use (EfficientNet, DenseNet, or VGG19) and specify which organ they are scanning. This flexibility allows users to test different models for the same organ or switch between organs.
3. **Image Scanning**: The selected model processes the input image based on the organ type. The app's backend leverages the pre-trained model to analyze the image and classify it as either healthy or diseased.
4. **Result Display**: The app displays the results, indicating whether the organ is healthy or, if a disease is detected, the name of the disease is displayed.

Key Results

- The application was successful in accurately classifying images based on the selected organ and model. Users were able to receive predictions for multiple organ types within seconds, demonstrating the system’s potential for real-time disease detection.
- The integration of EfficientNet, DenseNet, and VGG19 allowed users to compare results across different models, leading to flexibility in achieving high accuracy across various types of organs and diseases.

This Flask app serves as a prototype for a more extensive medical diagnosis platform, providing users with a user-friendly interface for multi-organ disease detection using advanced deep learning models.

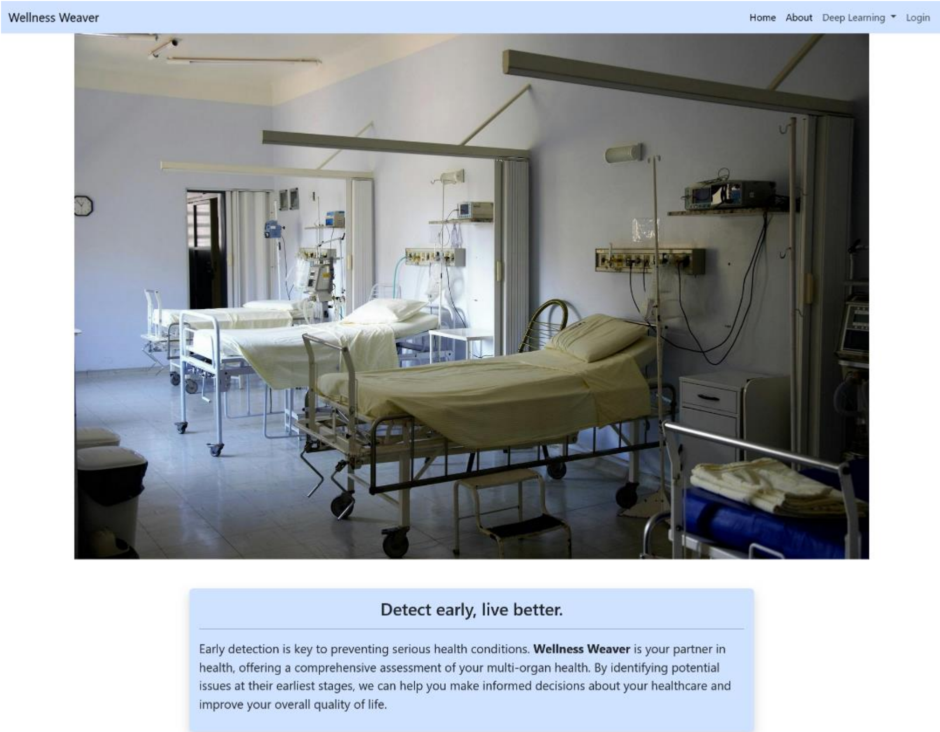


Figure 4: Flask App Home

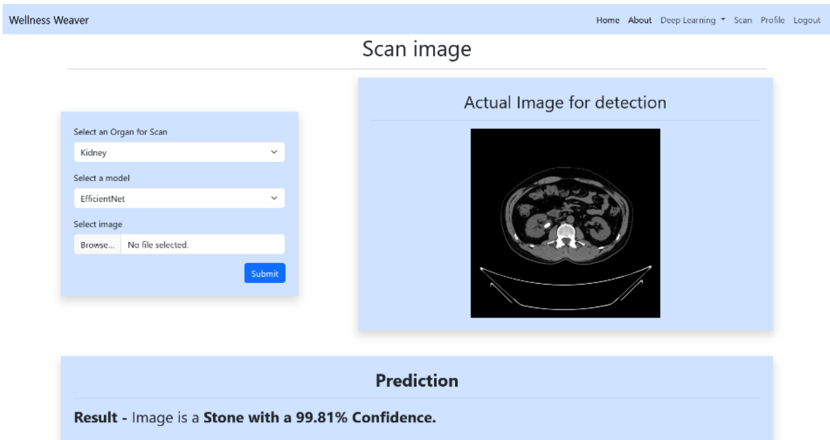


Figure 5: Image Scanning

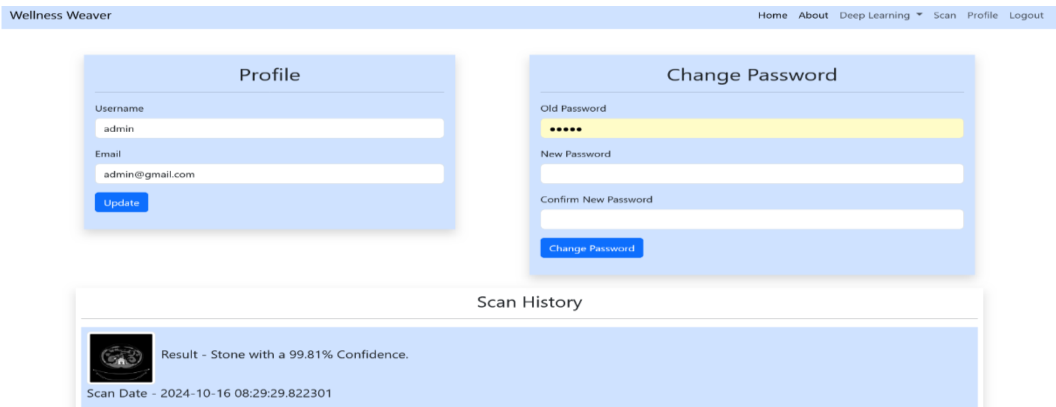


Figure 6: Profile with Scanning History

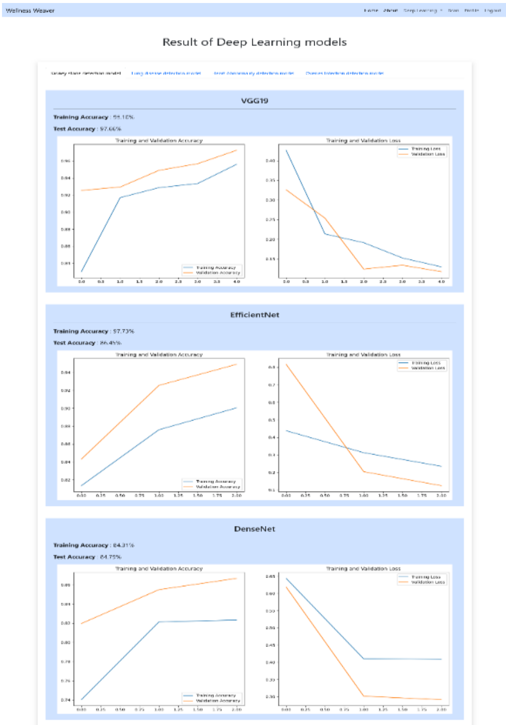


Figure 7: Training Results

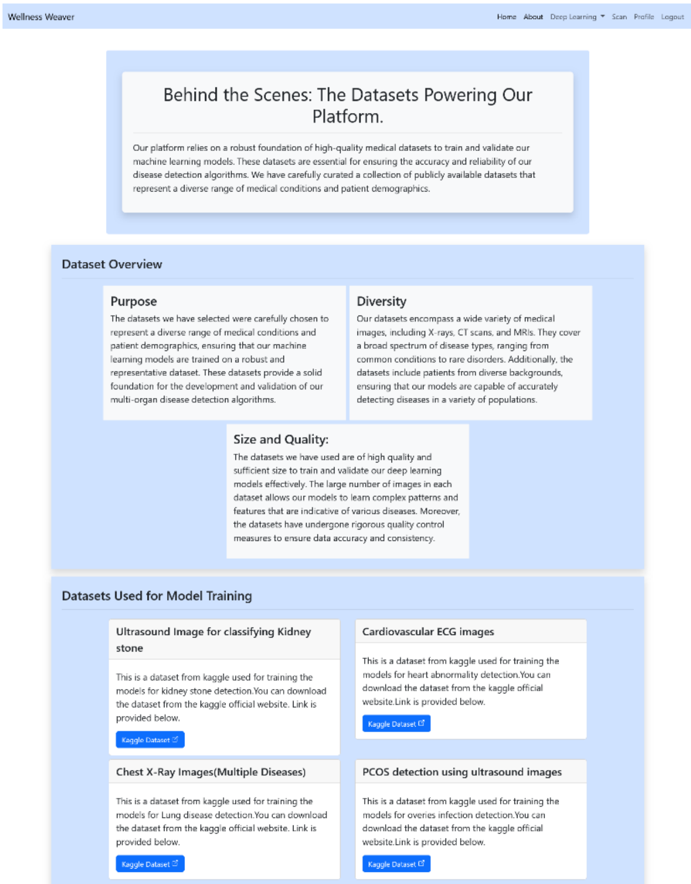
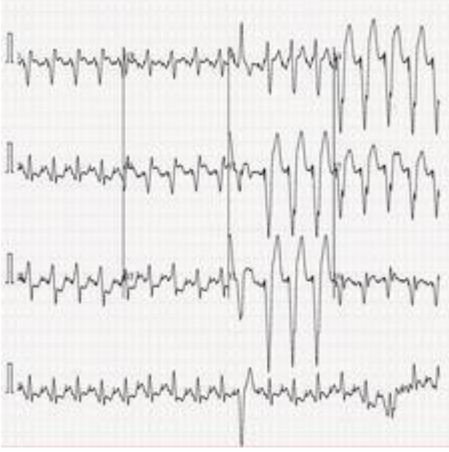
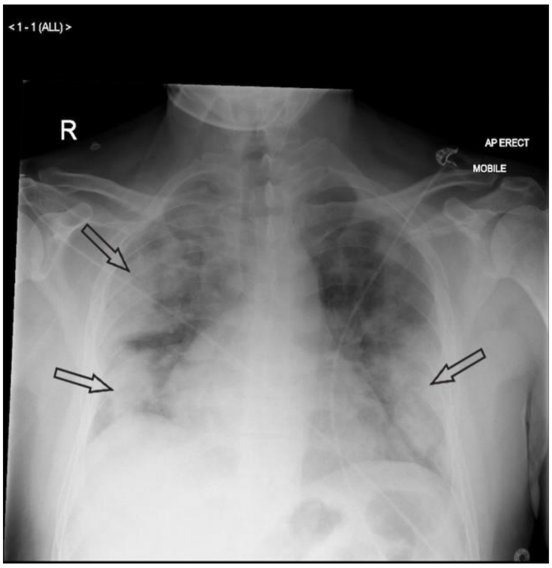
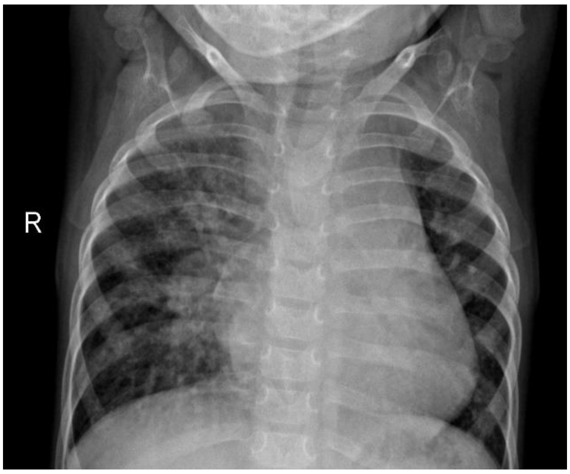
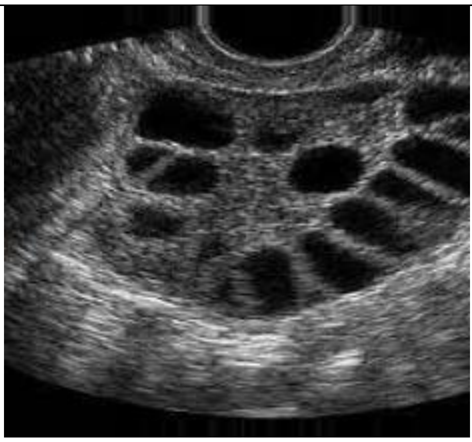
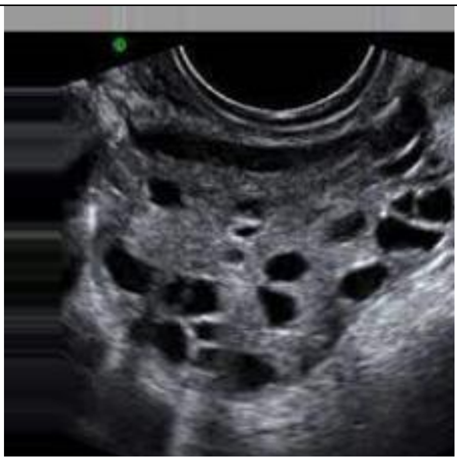
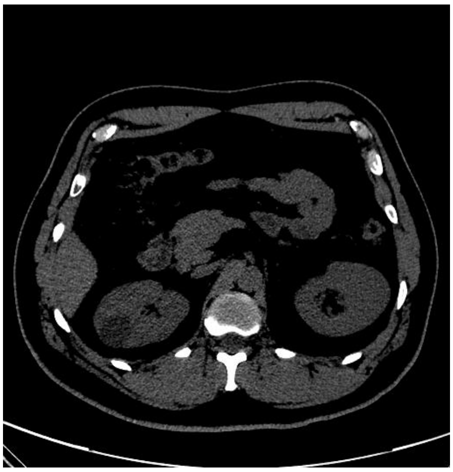


Figure 8: Dataset used for Research

Sl No	Disease Name	Image	Model Name	Model Accuracy
1	HB		EfficientNet	65.71%
2	Normal Heart		VGG19	65.67%
3	MI		VGG19	98.84%

4	Kidney Stone		EfficientNet	99.82%
5	Kidney Stone		DenseNet	64.22%

6	Covid		VGG19	95.21%
7	Pneumonia		VGG19	99.95%
8	Tuberculosis		DenseNet	88.24%

9	Ovaries Infection		EfficientNet	100%
10	Ovaries Infection		DenseNet	99.18%
11	Normal Kidney		VGG19	99.93%

12	Normal Lungs		EfficientNet	99.70%

Table 1: Multiorgan Disease detection using deep learning

V. CONCLUSIONS AND FUTURE WORK

The VGG19 deep learning architecture has proven to be highly effective for image classification tasks, especially in the context of medical image analysis for multi-organ disease detection. Its deep yet uniform structure, characterized by 3x3 convolutional filters and well-structured max-pooling layers, allows for efficient feature extraction and hierarchical learning. Despite its simplicity in design, VGG19 consistently delivers high accuracy and performance, making it a reliable choice for tasks requiring precise detection of subtle patterns in medical images. By leveraging pre-trained weights on large datasets like ImageNet, VGG19 can be adapted for specific medical applications, leading to quicker model training and better generalization on small or specialized datasets. The integration of VGG19 into clinical workflows holds great potential for aiding faster, more accurate disease detection and improving patient outcomes. However, while VGG19 offers strong performance, it also has limitations, including a high computational cost due to the large number of parameters and the significant memory footprint required during training and inference. These challenges present opportunities for optimization and improvement, paving the way for more efficient, scalable models.

Future Works

In Future, there are some alternative ways to express those points: VGG19, with its 143 million parameters, is resource-intensive, which makes it challenging to deploy on edge devices or in real-time clinical environments. Future work could focus on model compression techniques such as pruning and quantization to reduce the size of the network without sacrificing accuracy. Another approach could be exploring lightweight architecture such as MobileNet or EfficientNet as alternatives while maintaining the performance standards of VGG19. While VGG19 primarily focuses on image data, integrating multi-modal data, such as clinical notes, patient histories, and lab results, alongside medical images could enhance diagnostic accuracy. Future systems could use multi-input neural networks that combine both image and non-image data for a more holistic approach to disease detection. VGG19 has demonstrated strong performance in transfer learning applications, but there is potential to fine-tune it further for specific medical datasets. Research could focus on developing transfer learning techniques that adapt VGG19 to different imaging modalities (e.g., MRI, CT) and disease types, making the model more versatile across a wider range of diagnostic tasks.

While VGG19 excels in classification tasks, there is an opportunity to extend its capabilities to disease segmentation, allowing the model to not only classify diseases but also highlight affected areas within an organ. This could be achieved by integrating VGG19 with segmentation networks like U-Net or Mask R-CNN.

Moving beyond research, the next step would be integrating the VGG19-based multi-organ disease detection system into hospital information systems (HIS) and Picture Archiving and Communication Systems (PACS). Ensuring that the model is seamlessly integrated into real-world workflows while maintaining data privacy and regulatory compliance is a key area for future exploration.

REFERENCES

[1] K. Simonyan and A. Zisserman, 'Very Deep Convolutional Networks for Large-Scale Image Recognition', in *Proceedings of the International Conference on Learning Representations (ICLR)*, San Diego, CA, USA, 2015.

[2] M. Raghu, C. Zhang, J. Kleinberg, and S. Bengio, 'Transfusion: Understanding Transfer Learning for Medical Imaging', in *Proceedings of the 33rd Conference on Neural Information Processing Systems (NeurIPS)*, Vancouver, BC, Canada, 2019, pp. 3342–3352.

[3] R. H. Shen, W. Z. Yang, Y. K. Yu, and Z. L. Wang, 'Automated Detection of Lung Nodules Using Convolutional Neural Networks Combined with Transfer Learning', *IEEE Access*, vol. 8, pp. 105854–105863, 2020, doi: 10.1109/ACCESS.2020.3000620.

[4] M. A. Chowdhury et al., 'Lung Disease Classification Using Deep Convolutional Neural Network', *IEEE Access*, vol. 7, pp. 148951–148959, 2019, doi: 10.1109/ACCESS.2019.2944683.

[5] S. R. A. El-Rewaidy et al., '3D Convolutional Neural Networks for Automatic Cardiac Structure and Function Segmentation from 4D Cardiovascular Magnetic Resonance', *IEEE Transactions on Medical Imaging*, vol. 39, no. 9, pp. 2823–2834, 2020, doi: 10.1109/TMI.2020.2988444.

[6] Y. Lecun, Y. Bengio, and G. Hinton, 'Deep Learning', *Nature*, vol. 521, pp. 436–444, 2015, doi: 10.1038/nature14539.

[7] A. Esteva, B. Kuprel, and R. Novoa, 'Dermatologist-level Classification of Skin Cancer with Deep Neural Networks', *Nature*, vol. 542, no. 7639, pp. 115–118, 2017, doi: 10.1038/nature21056.

[8] S. Ioffe and C. Szegedy, 'Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift', in *Proceedings of the 32nd International Conference on Machine Learning (ICML)*, Lille, France, 2015, pp. 448–456.

[9] L. Yan, C. Zhang, and X. Xie, 'Blood Cell Image Classification Based on Deep Convolutional Neural Networks', *IEEE Access*, vol. 6, pp. 36188–36197, 2018, doi: 10.1109/ACCESS.2018.2846681.

[10] J. Deng, W. Dong, R. Socher, L. Li, K. Li, and L. Fei-Fei, 'ImageNet: A Large-Scale Hierarchical Image Database', in *Proceedings of the 2009 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Miami, FL, USA, 2009, pp. 248–255, doi: 10.1109/CVPR.2009.5206848.