VIT University

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MACHINE LEARNING ACCELERATED REAL-TIME BIOMEDICAL DATA ANALYSIS WITH VOC SENSOR INTEGRATION

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Guide:

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CONTENTS

Introduction

Pneumonia is a severe respiratory infection that affects millions of people globally. Early and accurate detection is crucial for effective treatment. Traditional diagnostic methods rely on radiologists' expertise, which can be time-consuming and prone to subjectivity. Deep learning, particularly Convolutional Neural Networks (CNNs), has shown significant promise in automating pneumonia detection using lung X-ray images. This project compares four CNN architectures—VGG16, MobileNetV2, DenseNet, and InceptionV3—to evaluate their performance in classifying pneumonia-affected lungs from normal ones.

Methods for pneumonia detection has evolved over the years, these include blood tests, xrays, MRIs etc. These conventional methods are usually harmful, painful and expensive. In our project we create a sensor-based device to provide a new approach to pneumonia detection through breath analysis. Through thorough research, it has been known that pneumonia can be detected by the spike of certain compounds in the exhaled breath of the patient, these include NO spikes, CO2 spikes (which flags the inflammation in the chest), and VOC compounds (Acetone, Ammonia, Ethanol, Methane etc).

Literature Review

1. Firmansyah and Setiadi, 2024 proposed a streamlined architecture that minimizes hardware programming complexity, enabling real-time multichannel ADC integration. Mostly this approach improves data acquisition efficiency and for IOT devices,can process simultaneous and diverse sensor inputs by giving high throughput and remote access capability.

2. Wavelet-based feature reduction techniques can be used to accelerate convolutional neural networks for hyperspectral image classification, which was proposed by Baba and Bonny, 2023. They implemented CNNs on an FPGA with a Micro-blaze processor, which achieved a 90% reduction in training time compared to CPU-based methods.

3. Altman and Wan, 2024 explored FPGA-based implementations of ML algorithms for biomedical applications. Thsification and regression models. They used FPGA to tackle obstacles and challenges like limited power, memory, and hardware resources while achieving high performance and scalability. The study underscores how FPGAs enable real-time processing and energy-efficient designs, making them suitable for applications such as genomics, medical imaging, and wearable devices.

4. Batista, Oberg and Saotome, 2024 introduced the use of DPR in FPGAs to optimize image edge detection for UAVs. They used Support vector regression for enhancing computational efficiency and achieved a 68-fold acceleration with lesser power consumption and hardware area.

5. Li, Wu, Sun, Yan and Zhang,2024 explored a groundbreaking approach to enhancing security in medical image transmission and storage. They proposed a new encryption process called 3D-PCHCS, which stands for 3D Pupal Equilibrium Curved Hyperchaotic System. This method involves embedding watermarks in the ROI using LSB technology and employing DCT for RONI processing. In this process they used FPGA to showcase real-time applicability. This analysis demonstrates strong flexibility against various attacks and invisibility.

6. Sivasankari, Ahilan, Kumar, 2023 introduced an innovative approach for edge detection for medical image processing, which compares edge detection algorithms with Gauss Gradient methods. There they highlighted the limitations of classical edge detection models in handling noise and demonstrates the robustness and efficiency of Gauss Gradient techniques in detecting edges in noisy medical images like CT and MR scans. They used Kintex-7 FPGA for real time processing and used Berkley database and medical images.

Literature Review

7. Sanjeev Sharma, 2023, explained an efficient approach to lossless medical image compression using FPGAs. He used Selfish Herd Optimization (SHO) algorithm to cluster image data based on anatomical features and combined with a DCNN to predict the pixel values. This process achieved a high compression ratio and also maintained the image quality. He used Virtex-7 and Virtex-5 FPGAs which reduced the power consumption and increased the frequency.

8. Lal, Chanchal, Kini and Upadhyay, 2024 underscored a process to grading renal cell carcinoma (RCC) using deep learning models on FPGA boards. They used models like LeNet, VGG-16, Inception-V3, ResNet-50, and DenseNet-169. The used FPGA for quantization and model optimization, which reduced computational complexity. This work underscores FPGA's potential in accelerating deep learning for resource-constrained applications, addressing latency, cost, and energy efficiency challenges in medical diagnostics.

9. Swetha, Karthika, Evangeline, Joy and Brintha, 2023, proposed a new algorithm based on Discrete Cosine Transform (DCT) technique for digital watermarking. The embedding of a digital watermark after the DCT, gave good and enhanced results. These experimental outcomes showed that the algorithm was safe from typical image analysis and malicious attacks. A DCT-based hardware accelerator was also designed for digital image watermarking. This preserved the original image quality while being resilient. This paper has highlighted the significant role of DCT-based watermarking in establishing the security and integrity side of biomedical images, especially in the medical industry.

10. Amdouni, Mtibaa, Gafsi, and Hajjaji, 2022, proposed a novel medical image encryption method that combined a chaos sequence with a modified Twofish algorithm. The encryption method, implemented on an FPGA platform, ensured high security and performance for the encryption and decryption of medical images. The mentioned algorithm utilized chaos-based encryption and the Twofish algorithm to ensure secure image encryption. The experimental evaluation on an FPGA demonstrated its good performance and reliable security. This study showed the potential of an FPGA-based cryptosystem, for secure and efficient medical image handling.

11. Vidyadhar, Mahalakshmi, Kethan and Deepak, 2023, focused on implementing a medical image fusion, using Principal Component Analysis (PCA) on an FPGA platform to combine CT and MRI scans for improved diagnostic accuracy. This PCA-based image fusion technique has successfully enhanced medical images by combining the features with highest information content from the input images. The FPGA implementation exhibited the highest quality metrics when compared to other architectures, including DWT-based approaches. This indicates superior performance in terms of image clarity and diagnostic utility.

Literature Review

12. Baali, Bourbia, Messaoudi, and Bourennane, 2024, presented a parallel hardware architecture for medical image processing using the Xilinx System Generator (XSG), which integrates with MATLAB-Simulink and the Xilinx Vivado synthesis tool. They proposed a new memory management strategy which uses 3x3 shift registers to optimize the FPGA's resource utilization during the implementation of an edge detection algorithm. The proposed approach demonstrated significant reductions in resource utilization, compared to prior implementations, emphasizing its efficiency in optimizing the FPGA memory management for edge detection algorithms.

13. Ghayoula and Amara. (2024) implemented the RSA-1024 algorithm on an Artix-7 FPGA, to enhance medical imaging security. They used the square and multiply method for modular exponentiation, and VHDL for deployment. The design had achieved improved efficiency and security. While demonstrating significant advancements, the study noted the limitations with Artix-7, suggesting future exploration of advanced FPGA platforms for better and scalable security solutions.

14. Bouganssa and Sbihi, 2016 presented an algorithm for adaptive edge detection for medical image processing and tumor characterization on FPGA. They utilized Xilinx Spartan 6 FPGA which had gradient calculation combined with intelligent thresholding. Their work demonstrated an effective edge detection and tumor characterization while maintaining the output capabilities of VGA output which made it very suitable for high speed computer vision applications.

15. Haldorai and Lincy, 2024 proposed an image segmentation technique using the VLSI technology which was implemented using the Xilinx System Generator (XSG) and FPGA. They demonstrated superior performance compared to the other conventional programmable digital signal processors and PCs with coprocessors in terms of the design time, cost effectiveness and speed. They achieved an excellent route delay and very low power consumption while utilizing only 2% of the available device space.

16. Bal and Das, 2018 proposed a medical image watermarking technique to combat copyright infringement in medical imaging using FPGAs. They embedded an encrypted watermark in the least significant bits of the image pixels, this method ensured imperceptibility and robust security. This approach was successful in providing copyright protection and medical image integrity which offered scalable and hardware efficient solutions for the healthcare domain.

17. Ravi and Sewa, 2019 developed an algorithm for tomographic image reconstruction using an FPGA accelerated maximum likelihood expectation maximization (MLEM). They utilized Virtex 7 VC709 FPGA and achieved excellent speed improvement over CPU based methods. They outperformed other GPUs and CPUs in the energy consumption, speed and flexibility for real time medical imaging.

Literature Review

18. Ahmad and Ja'afar, 2012 proposed a 3D Daubechies wavelet transform with two transpose memories for medical image compression using the Altera Cyclone II FPGA for processing the 3D medical images. They achieved a better area efficiency, a superior performance in power consumption and maximum frequency. This architecture proved to be very suitable for real time medical imaging applications which required efficient compression.

19. Samantaray and Edavoor, 2023 proposed a novel Dyadic Gabor Wavelet Filter Bank (DGWFB) which was implemented using a FPGA for power efficient medical image retrieval. They performed tests across three medical datasets which demonstrated enhanced retrieval precision and rate. They reduced power consumption, computational complexity and hardware requirements while improving the processing time.

20. Natesan and Siddeeqa, 2022 conducted a few surveys based on FPGAs for medical image processing techniques for cancer detection, focusing on brain, liver and breast tumours. They utilized some advanced approaches like 3D ultrasound tomography and Monte Carlo simulation to highlight the strengths and limitations of various methods. They worked on improving diagnostic accuracy, real time imaging performance and noise reduction for early cancer detection.

21. Raj and Karthick, 2023 developed an image encryption system using a vedic multiplier for diffusion and a linear feedback shift register (LFSR) by utilizing Intel Cyclone III FPGA. They achieved a reduced power dissipation, optimized resource utilization and enhanced encryption security validated through statistical and randomness tests for the developed system. They offered an efficient, secure and a scalable solution for safeguarding sensitive medical image data.

Problem Foundation

The primary challenge in pneumonia detection is distinguishing between healthy and infected lungs using chest X-rays and breath biomarkers. Key differentiators include:

- Radiographic Abnormalities: Pneumonia-infected lungs show increased opacity (white patches) and altered texture patterns on chest X-rays, detectable using CNN-based deep learning models.
- Breath Biomarkers: Infected individuals exhale abnormal levels of VOCs, CO_2, and NO, which can be detected using embedded gas sensors as non-invasive indicators of respiratory distress.

Our objective is to develop and compare different CNN models to identify pneumonia effectively with high accuracy and computational efficiency while integrating real-time breath analysis through hardware for hybrid diagnostics.

Our device uses sensor configuration to detect these spikes from the exhaled human breath and further detect anomalies in said compounds to find pneumonia by comparing the values from their biomarkers.

Relevance to Sustainable Development Goals (SDGs)

1. **SDG 3 – Good Health and Well-being:**
   Enables early, accurate, and non-invasive pneumonia detection, improving healthcare outcomes and reducing mortality, especially in underserved and rural areas.

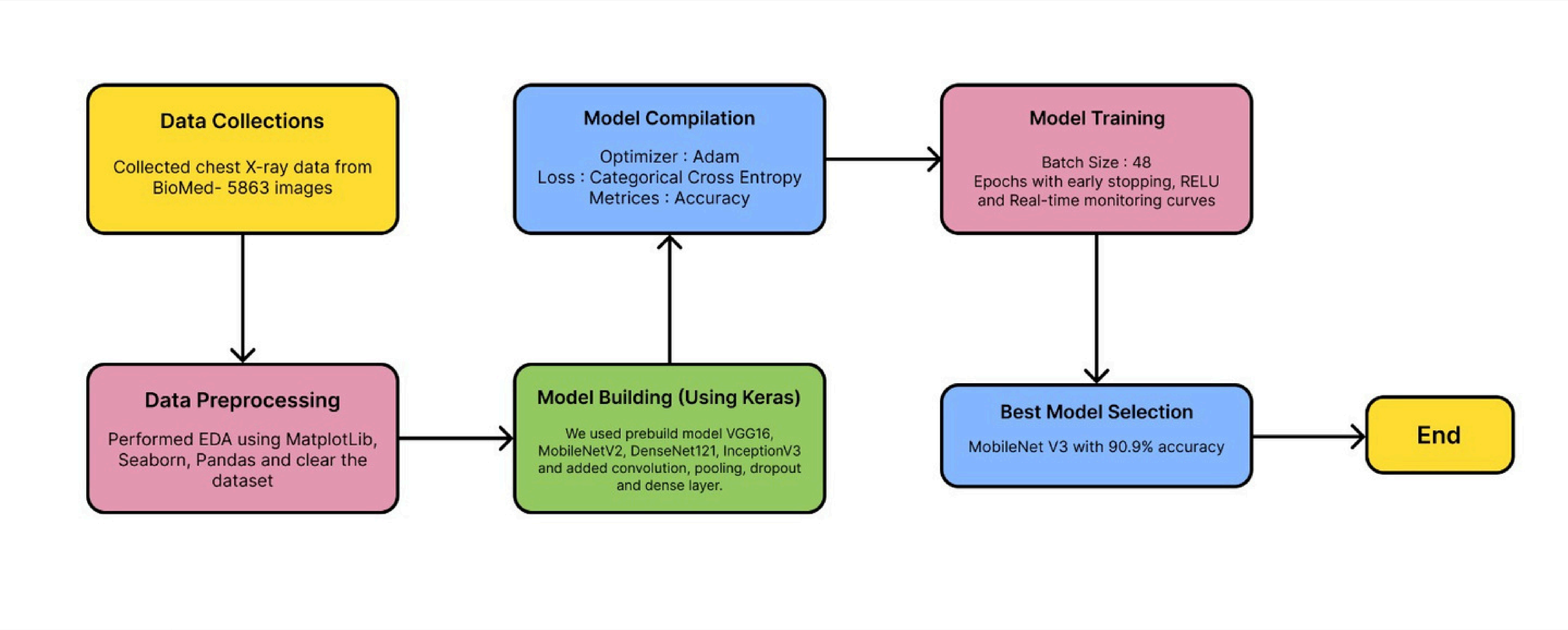
2. **SDG 9 – Industry, Innovation, and Infrastructure:**
   Introduces a novel hybrid diagnostic solution by integrating AI-based imaging with real-time breath analysis on embedded hardware, promoting innovation in low-cost medical devices.

3. **SDG 10 – Reduced Inequalities:**
   Provides an affordable and portable diagnostic system that addresses disparities in access to quality healthcare between urban and remote regions.

4. **SDG 4 – Quality Education (Indirect Impact):**
   Encourages interdisciplinary research and hands-on learning in biomedical engineering, AI, and IoT, promoting innovation-driven STEM education and development.

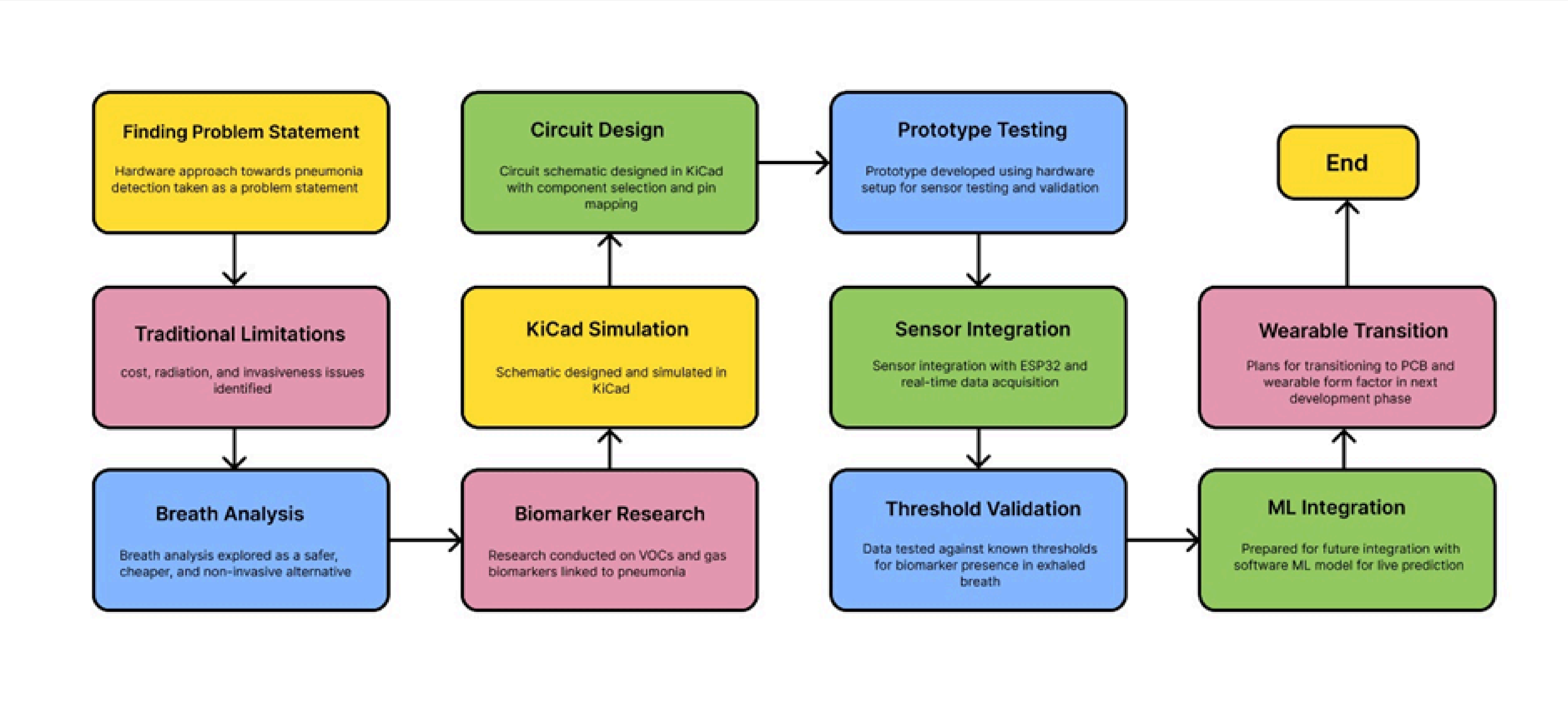
Proposed System

This project follows a systematic pipeline for pneumonia detection using chest X-rays. Initially, 5863 images were collected from the BioMed dataset. Data preprocessing was done using EDA tools like Matplotlib, Seaborn, and Pandas to clean the dataset. Several CNN models (VGG16, MobileNetV2, DenseNet121, InceptionV3) were built using Keras, incorporating convolution, pooling, dropout, and dense layers. The model was compiled using Adam optimizer and Categorical Cross Entropy loss with accuracy as the metric. Training was conducted with batch size 48, RELU activation, early stopping, and real-time monitoring. Finally, MobileNetV3 achieved the best accuracy of 90.9%, selected for deployment.



Proposed System

The prototype of this device is to create it into a custom pcb with a smaller microcontroller utilising wifi modules for remote communication. This device with its sensors will then be connected to a wall of filters which blocks any foreign particles from damaging the sensors or tampering with its readings. A filter foam is then used with its input attached to a mask with ventilation holes. This mask will be the entry source of our readings through which every breath will be read after filtering.



Analytical and Theoretical Description

1. Model Development and Dataset Overview

Four pre-trained CNN models—**MobileNetV2**, **VGG16**, **DenseNet121**, and **InceptionV3**—were fine-tuned using a pediatric chest X-ray dataset of 5,863 images (1,341 Normal, 4,522 Pneumonia) sourced from Mendeley Data. Data augmentation addressed class imbalance. Models were trained using the Adam optimizer and categorical cross-entropy, with dropout, batch normalization, and learning rate scheduling to prevent overfitting and ensure robust performance.

2. Evaluation Metrics and Performance:

Models were evaluated using **accuracy**, **precision**, **recall,** and **F1-score**, along with confusion matrices. Among them:

- **MobileNetV2** achieved the best accuracy of 90.9%, offering a balance between performance and computational efficiency—ideal for embedded deployment.
- **VGG16** followed closely at **90.2%**, known for its simplicity and feature extraction power.
- **DenseNet121** (88%) and **InceptionV3** (86.2%) also performed well but were comparatively less efficient

Analytical and Theoretical Description

3.Hardware Compatibility:

MobileNetV2 was identified as the most suitable model for on-device inference, due to its low parameter count and high inference speed—making it compatible with low-power devices like ESP32

We use a microcontroller(esp32) at the heart of our device to power, control and analyse the input from our sensors. These inputs are later read by a code over the Arduino ide where the results are shown with the biomarkers kept in mind. As the sensors all work at different voltage source, we use two 3.3V lithium ion batteries (lightweight, rechargeable, low self discharge, long lasting) in series which give us a rough input of 7.4 volts which is further tuned down to 5v by a buck converter. This powers the esp32 and further the MiCs 5524 (VOC sensor) and MiCs 2714(NO2 sensor). The SCD40 D R2(CO2) sensor is powered by a stable voltage from the esp32, these are further connected into the gpio and i2c connections which enables us to read the values they obtain. Capacitors are used for input output filtering. Resistors are used in the circuit as voltage dividers and pull up resistor for the I2C communication.

Hardware/Software Tools & Design Parameters

Hardware Used:

- KiCad (Schematic design)

Software Tools:

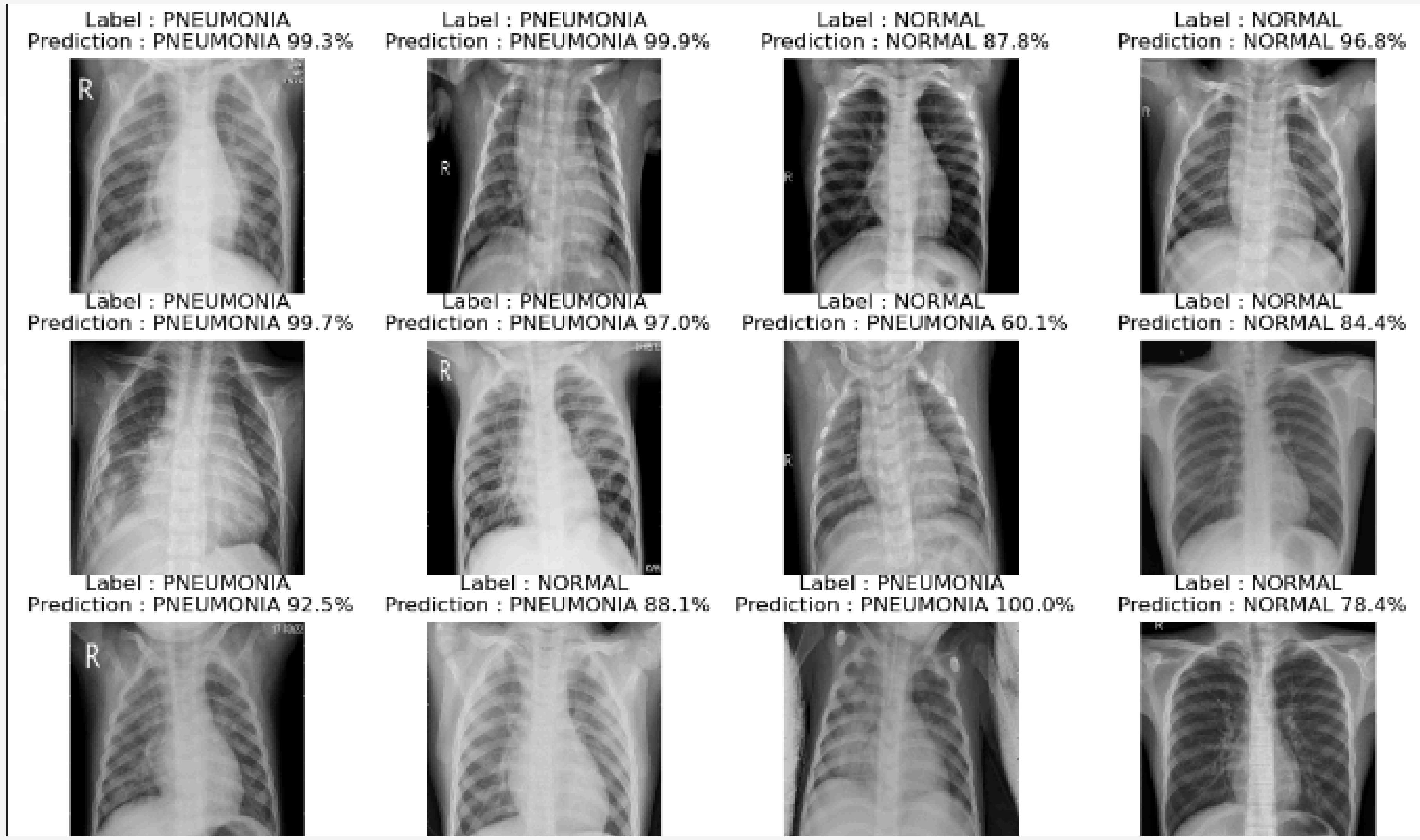
- Python, TensorFlow, Keras
- OpenCV for image processing
- Matplotlib & Seaborn for visualization

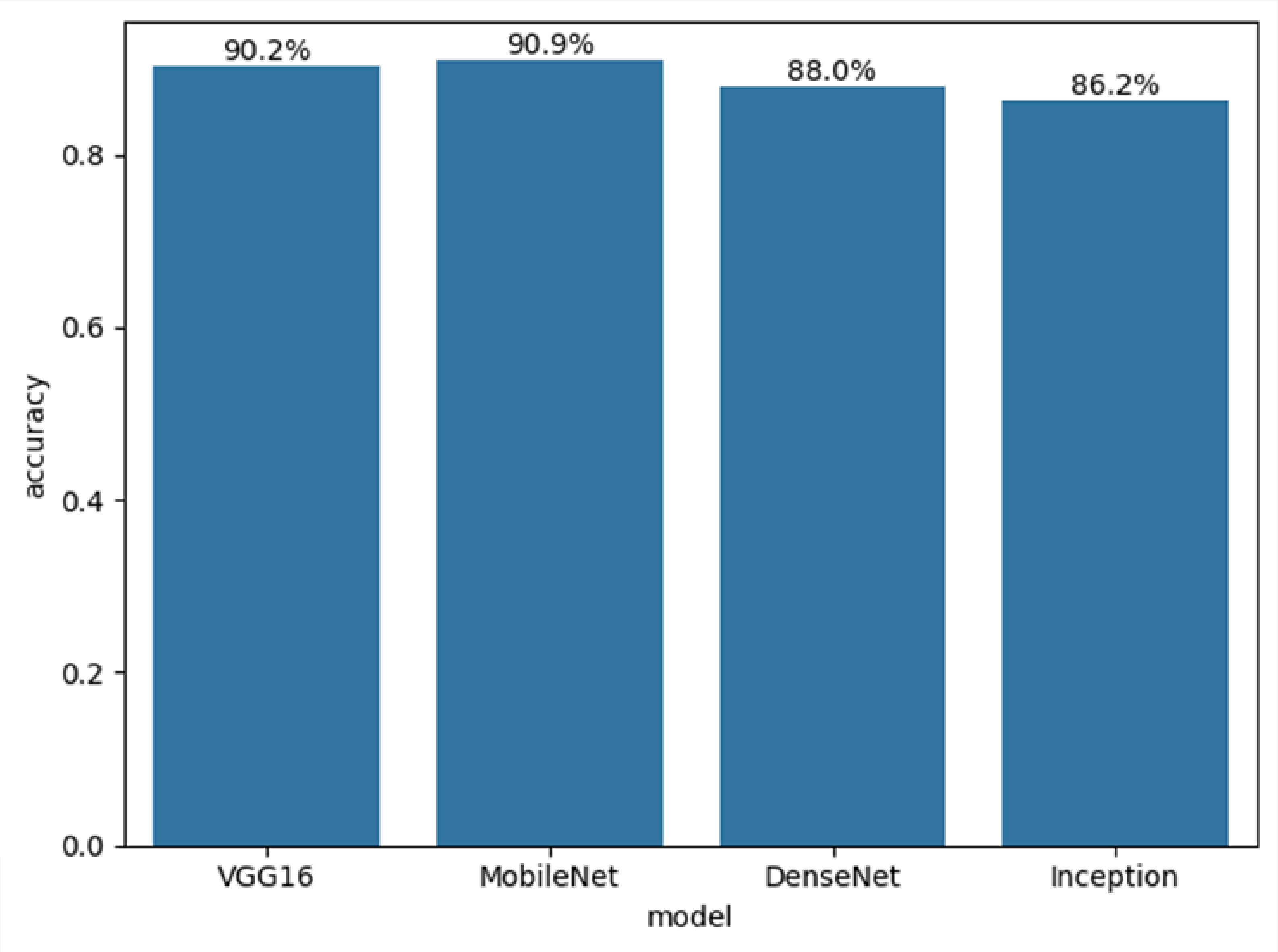
Design Parameters:

- Batch Size: 32
- Epochs: 50
- Loss Function: Categorical Crossentropy
- Optimizer: Adam

Results analysis

Software





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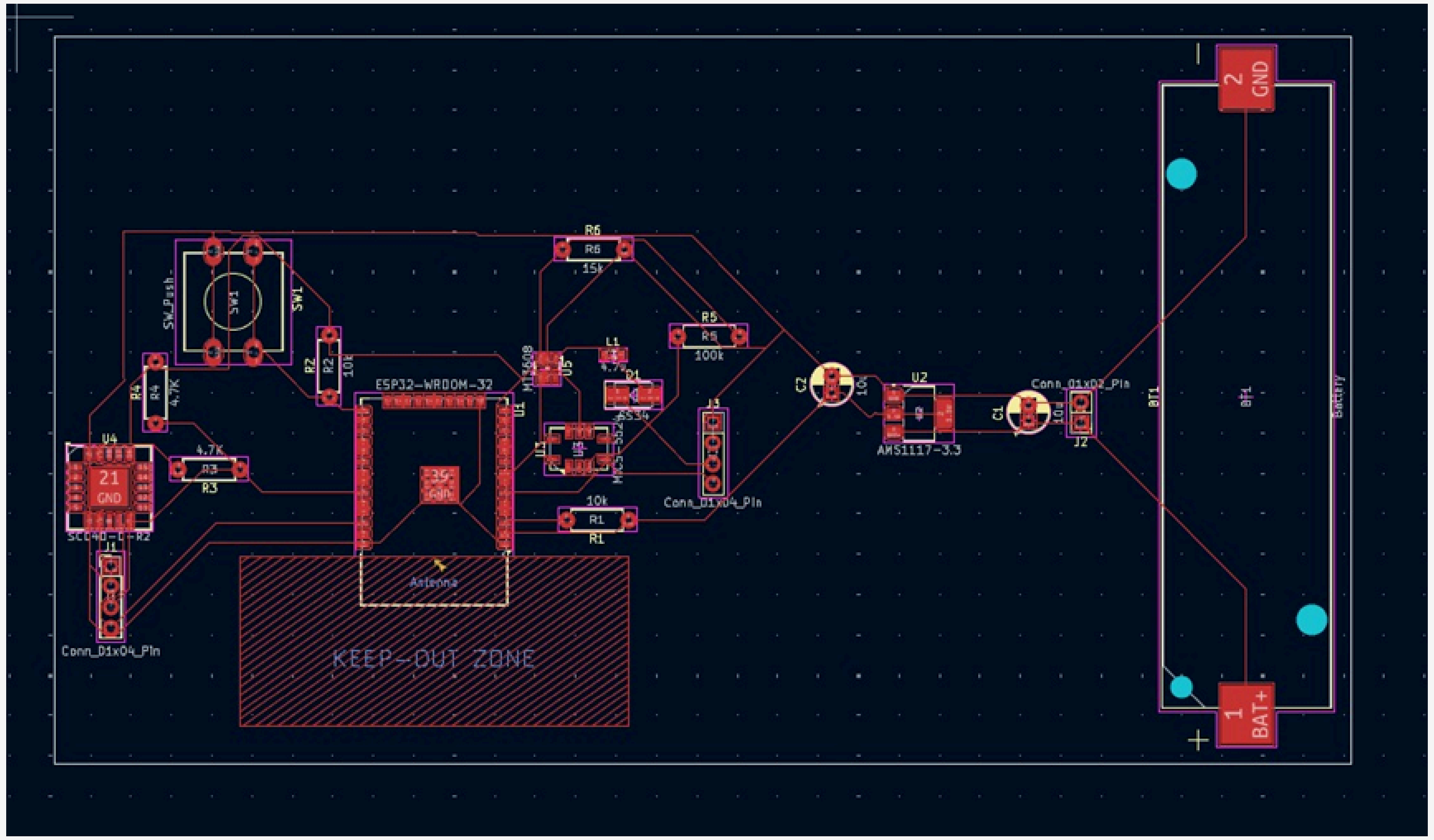
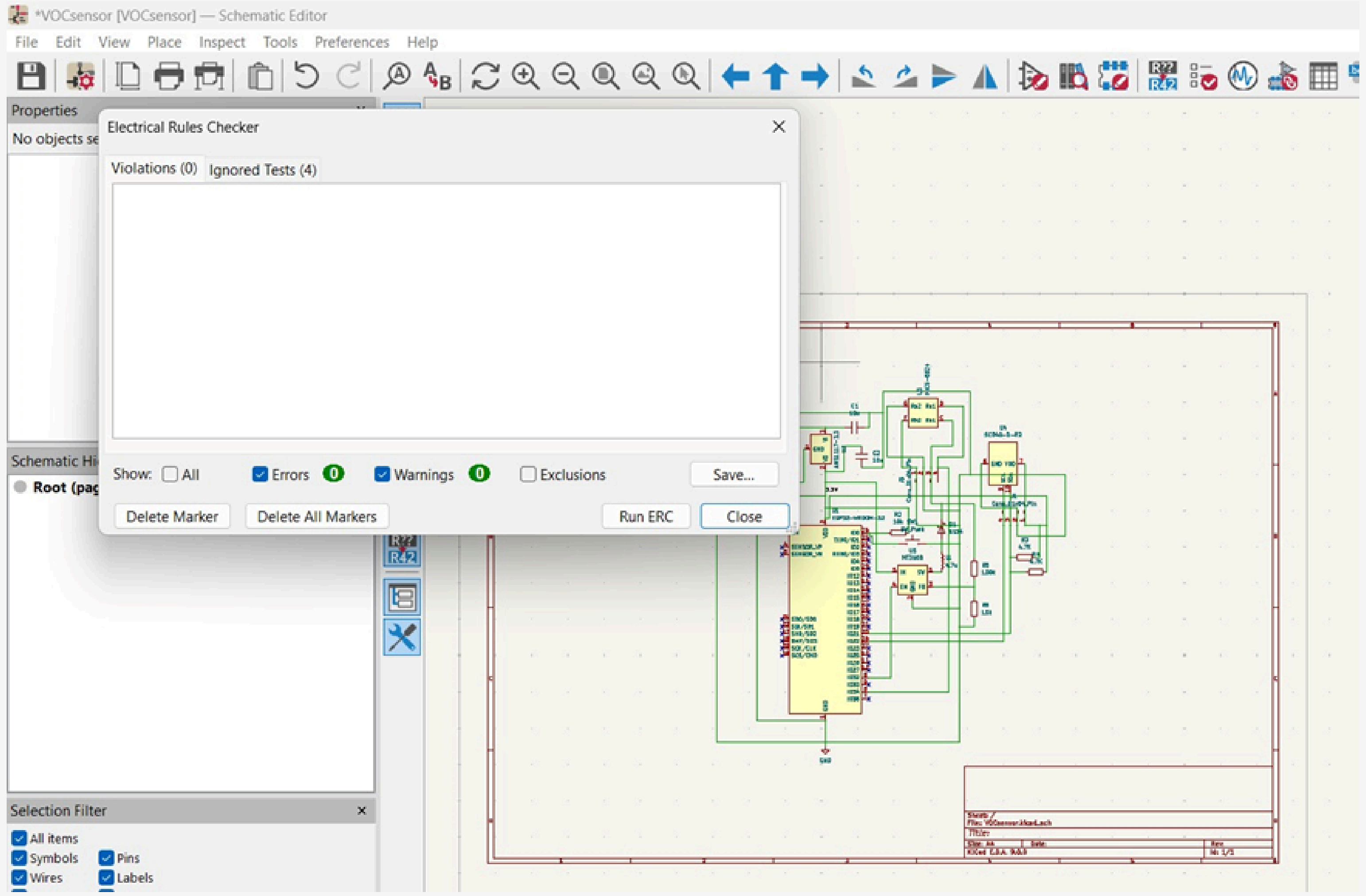
Results analysis

Hardware





Contribution of individual Team members

Rupam Mal – Software Development

Handled the entire software side, including building and optimizing deep learning models like VGG16, MobileNetV2, DenseNet121, and InceptionV3 and worked on data preprocessing, model training, evaluation, and performance comparison using metrics like accuracy and F1-score.

Harsh Kumar – Cross-Support & Documentation

Synthesized the inputs from software and hardware domains into a unified narrative and bridged both technical and non-technical aspects ensured the project was well-articulated, professionally presented, and submission-ready and assisting in debugging model training issues and hardware design planning.

Debtonu Bose – Hardware Development

Worked on the hardware prototype for detecting VOCs from breath and integrated sensors (VOC, NO_2, CO_2) with the ESP32 microcontroller, designed the power circuit, and set up the data reading system for real-time detection.

Conclusion

This study highlights the effectiveness of deep learning for pneumonia detection using chest X-rays. Using CNN architectures—MobileNetV2, VGG16, DenseNet121, and InceptionV3—we achieved classification accuracies of 90.9%, 90.2%, 88.0%, and 86.2%, respectively. MobileNetV2 performed best. Transfer learning significantly enhanced model accuracy, making them suitable for real-time clinical deployment. With minimal false positives and negatives, the models aid fast, reliable diagnosis, reducing workload and improving patient outcomes. This work demonstrates the potential of AI-based tools in medical imaging, promoting early detection and better healthcare accessibility through integration with real-time diagnostic systems.

This device enables us to eliminate the traditional blood drawing method and the exposure to radiation from xrays, and can be frequently used as the first step to pneumonia detection.
Further integration of the device may also help us understand the types of pneumonia(viral or bacterial) by using high end sensors with more accuracy and will help us develop an environment friendly and sustainable approach to detection of diseases from breath analysis.

Impact of the project on society and environment

The project offers a transformative impact on society by enabling affordable, non-invasive, and accessible pneumonia diagnosis, especially in rural and under-resourced areas. By reducing dependence on expensive radiological tests and trained specialists, it promotes healthcare equity. Environmentally, the use of low-power, portable hardware minimizes energy consumption and radiation exposure. Early detection reduces hospital stays and medical waste, contributing to sustainable healthcare. The integration with IoT also supports remote monitoring, aligning with eco-friendly and inclusive digital health innovations.

Project Outcome(Publication/Patent details)

4 of 128

5th IEEE International Conference on VLSI Systems, Architecture, Technology and Applications : Submission (187) has been created. External Inbox ×

Microsoft CMT <email@msr-cmt.org>
to me

Mon, Mar 17, 7:06 AM

Hello,

The following submission has been created.

Track Name: VLSISATA2025

Paper ID: 187

Paper Title: Machine Learning Accelerated Real Time Biomedical Data Analysis – Pneumonia Detection

Abstract:
In recent times, medical image analysis using deep learning has shown significant advancement in automated disease detection. This study shows a deep learning-based approach for classifying chest Xray images to detect pneumonia normal or abnormal. We have applied multiple CNN architectures like VGG16, MobileNetV2, DenseNet121 and InceptionV3 and to improve classification accuracy, we use transfer learning techniques. We calculate performance metrics like accuracy, precision, recall and F1 score, by which we can compare the effectiveness of this architecture. As per our results, we find that MobileNetV2 achieves the highest classification accuracy of 90.9%, followed by VGG16 (90.2%), DenseNet121 (88.0%) and InceptionV3 (86.2%). These results highlight the potential of CNN based architectures in assisting healthcare professionals with fast and accurate Xray diagnosis, reducing errors and improving patient outcomes.

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Secondary Subject Areas: Not Entered

Submission Files:
final paper_harsh.pdf (442 Kb, Mon, 17 Mar 2025 01:35:43 GMT)

Submission Questions Response: Not Entered

Thanks,
CMT team.

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