IMAGE-BASED ABDOMINAL INJURY DETECTION USING DEEP LEARNING

A Capstone Project report submitted

in partial fulfillment of requirement for the award of degree

BACHELOR OF TECHNOLOGY

in

SCHOOL OF COMPUTER SCIENCE AND ARTIFICIAL INTELLIGENCE

by

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CERTIFICATE

This is to certify that this project entitled "**Image-Based Abdominal Injury detection using Deep learning**" is the bonafied work carried out by **BAIRI RAGHAVENDRA,BOGA VIGNESH SATHISH,GOUNDLA SAI HASINI, JAKKAM VINAY KUMAR** as a Capstone Project for the partial fulfillment to award the degree **BACHELOR OF TECHNOLOGY** in **School of Computer Science and Artificial Intelligence** during the academic year 2024-2025 under our guidance and Supervision.

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TABLE OF CONTENTS

S.No	Topics
1.	Abstract
2.	Introduction of Project
3.	Problem Statement
4.	Literature Survey
5.	Requirement Analysis and Risk Analysis
6.	Proposed Solution, Approach and Technologies
7.	Architecture Diagrams, Flow Chart and DFD
8.	Simulation Setup and Implementation
9.	Results Comparison and Analysis
10	Learning Outcome
11.	Conclusion and Challenges
12.	References
13.	Links and Details about Other Artifacts

LIST OF FIGURES

S.No	Figure Name
1.	Data Flow Diagram (DFD)
2.	UML Use Case Diagram
3.	Flow chart
4.	confusion matrix of Abdominal Injury Detection System
5.	Grad-CAM Result Visualization of Trauma Areas.
6.	Radar Chart of Performance Metrics Comparison.
7.	Accuracy of Model validation and loss per epoch
8.	Model prediction probabilities
9.	Saliency Map pixel importance

LIST OF TABLES

S.No	Abdominal Injury Detection Table Name
5.2	Risk analysis and mitigation strategies
6.3	Hardware and Software Configuration for Simulation Setup
8.3	System Testing and Validation Results
9.1	Machine Learning Model Performance Metrics (Accuracy, Precision, Recall, F1-Score)
9.2	Confusion Matrix for Trauma vs. No Trauma Classification
9.7	Comparison of Existing Diagnostic Systems and Proposed AI System

LIST OF ACRONYMS

Acronym	Full Form / Description
AI	Artificial Intelligence
CNN	Convolutional Neural Network
CT	Computed Tomography
MRI	Magnetic Resonance Imaging
Grad-CAM	Gradient-weighted Class Activation Mapping
GPU	Graphics Processing Unit
Flask	Lightweight Python Web Framework
API	Application Programming Interface
TP / TN / FP / FN	True Positive / True Negative / False Positive / False Negative
F1-Score	Harmonic Mean of Precision and Recall
ML	Machine Learning
DFD	Data Flow Diagram

1.ABSTRACT

The Abdominal trauma is one of the most difficult medical crises to treat. They need a fast and proper diagnosis in order to avoid severe complications. Conventional manual inspection of medical images is simply excessively time-consuming. It also poses the risk of human mistakes, particularly when dealing with emergency operations that are mostly busy. In our project, the proposed AI system is meant to identify abdominal injuries. It is based on deep learning and Grad-CAM techniques of visual explanation.

This system is based on a Convolutional Neural Network. It chooses EfficientNet-B0 as the core architecture. The training occurs on the set of labeled medical images. These enable the model to categorize scans into Trauma or No Trauma. The model computes the likelihood of an abdominal trauma after handling input images. It has a high degree of accuracy in this task. In order to enhance clarity and credibility we also include Gradient-weighted Class Activation Mapping, which is referred to as Grad-CAM. This will produce heatmaps to indicate the areas of concern affecting the decision that is made by the model. All in all, it makes the system more decipherable to ensure useful application by the doctors.

Our web interface has been designed on Flask. Users post their medical photographs via it. They get the results of prediction nearly instantly. They also watch images of the afflicted areas. The interface gives priority on crucial user features. It remains easy and user friendly especially among medical practitioners. In order to measure the performance of a model, we consider accuracy, precision, recall, and F1-score. We also provide such charts as confusion, radar, and graphs of validation tests.

All this framework shows how Artificial Intelligence can be used to aid radiologists. It allows quicker identification of the abdominal injuries more accurately. It saves on time in diagnosis. It also enhances patient treatment decision making. The project enhances the application of smart AI in medical imaging. These instruments can be understood and work effectively.

2.INTRODUCTION

In medical diagnostics, abdominal injuries are crucial in saving lives and particularly where this detection is used in trauma and emergency care. The symptoms of the internal injuries do not always have a rapid diagnosis due to the complex nature of the abdominal trauma that do not manifest themselves in the initial period. Diagnosis used to be done manually by radiologists or doctors who interpret medical images in form of CT scans and X-rays. Manual interpretation however is time consuming, prone to human error and can cause delays in the treatment of acute cases. The combination of the Artificial Intelligence (AI) and Deep Learning (DL) methods has demonstrated a new direction of more efficient and reliable medical image analysis in order to handle such challenges.

The project is named Abdominal Injury Detection using Deep Learning and is aimed at creating an artificial intelligence-based application that could detect the existence of abdominal damage through medical photography. The model is implemented with the help of Convolutional Neural Networks (CNNs) which are a type of deep learning algorithm that is highly effective when it comes to solving image recognition problems. In particular, the system relies on EfficientNet-B0 architecture which balances well between the accuracy of a model and its computational efficiency. The trained model is able to categorize the provided image in either of two categories: Trauma or No Trauma using learned features on the dataset.

Among the important features of this project, the introduction of Grad-CAM (Gradientweighted Class Activation Mapping) is also worth mentioning since it uses a graphical representation to illustrate the areas on the image, which the model concentrates on during its prediction. This makes it transparent, interpretable and the medical practitioners can understand and be assured of the outputs of the system. The heatmaps visualization helps us to understand the decision-making of the AI model, which allows closing the gap between machine intelligence and clinical reasoning.

It also involves the project of a Flask-based web application, in which the user can simply upload medical images, watch predictions, and heatmap overlays in real-time. This easily accessible user interface is developed on HTML, CSS, and JavaScript, which guarantee easy usability and interplay. Besides training models, the performance of model training measures, including accuracy, precision, recalls, F1-score, and visual aids, including confusion matrices, radar charts, and validation graphs, are evaluated to determine and guarantee reliability.

In emergency and trauma care, medical diagnostics needs the timely and precise identification of abdominal injuries. Traumas in the abdominal area are frequently complicated and do not manifest immediately after the accident or a physical trauma. The biggest obstacle in those situations is that internal bleeding or the destruction of some organs may not be noticed during the early stages of analysis. Traditionally, the process of detecting such injuries is in the jurisdiction of radiologists or physicians who are forced to physically inspect the medical images obtained during CT scans or X-rays. Although this manual inspection has rather satisfactory outcomes, it is time-consuming and can be associated with human error. It could postpone important interventions particularly in situations that are life threatening. As the number of cases of traumas rises continuously across the globe, the need to have diagnostic assistance that can be quick and accurate has grown much more urgent. One of the promising solutions answering these challenges seems to be the strategic implementation of Artificial Intelligence (AI) and Deep Learning (DL) in this area to provide a high level of efficiency, accuracy, and speed in the medical image analyses.

The project of Abdominal Injury Detection using Deep Learning is aimed at creating the intelligent system that is able to detect abdominal trauma in medical imaging. Deep learning and Convolutional Neural Networks (CNN) have become of great use in image-processing tasks because it is capable of identifying patterns and features in large datasets automatically without human supervision. The specific architecture chosen in this project is the EfficientNetB0 that is an incredible trade-off of cost of computation and performance. EfficientNet models are made to be highly accurate and the resource consumption is low- a rather significant aspect in creating scalable and deployable medical AI systems. The model created within the framework of this project categorizes pictures into two groups: Trauma or No Trauma so that it should be able to make a quick diagnosis and help the medical personnel to prioritize the treatment of patients.

One of the most glaring aspects of this system is the adoption of Grad-CAM that improves the model interpretability to an enormous extent. Grad-CAM does not only give a label prediction, but visually indicates which part of the image affected the decision of the model. Such heatmaps can help clinicians to know not only the outcome, but also the reasoning of the outcome. This is important in clinical settings where trust, transparency and justification are obligatory. The system helps to fill the gap between machine intelligence and medical expertise and makes AI a supportive tool and not a black-box mechanism. By so doing, it puts radiologists in a position where they can be able to confirm the predictions done by AI.

The other important point of this work elaborates on the creation of a web application built on Flask and will allow uploading medical images and getting live predictions. To create a web page that is easy to use, more interactive, and responsive, a basic interface was created using HTML, CSS, and JavaScript. Hence, it simplifies and streamlines the process of the use of the system, even among those individuals who cannot be proud of the possibility to operate the complex AI tools. This way, through a clean and user-friendly interface, the medical professional can engage with the model, visualize areas of injuries, and interpret the results of prediction in real-time, which makes the system appropriate to a clinical and educational environment.

Other than model deployment, the performance evaluation is also highly emphasized by this project. The accuracy, precision, recall, and F1-score are several measures, which are applied to assess the reliability of the model. Graphical programs such as confusion matrices, radar charts, and training-validation graphs are important in giving insights on the critical aspects of modeling behavior, its strengths, and potential limitations. All these aspects of assessment make this system not only functional but also scientifically viable and sound to be applied in reality. Not only does this contribute to a technical level but it is also essential to the bigger picture of ensuring the accessibility of AI in the healthcare domain. A variety of medical facilities particularly in the less developed segments of the world might lack the additional computing powers or the advanced equipment. This system can be implemented even in lowresource settings because of the use of EfficientNet-B0 and lightweight web technologies. This will make sure that the advantages of AI, especially quick screening and decision support, can be available to the hospitals and clinics, which will require them the most. Thus, the study is a good foundation to any future advances in the area of medical diagnostics using computers. Through improvements in this system, multiplex classification is possible to classify a number of abdominal injuries, detect abnormalities of specific organs, or even rely on the multimodal imaging data. Such improvements would make it much more applicable clinically and would lead to the further development of modern health care thanks to AI.

3.PROBLEM STATEMENT

The existing procedure of abdominal injury diagnosis is significantly based on manual assessment of medical imaging like CT and MRI. This process is costly in time and can be subject to human error and also requires availability of radiologists and their competency. Delays in the detection of internal abdominal trauma lead to life-threatening complications or even death in case of emergency situations.

The current systems are not typically automated, interpretable, and fast decision-makers, thus the diagnostic process is not efficient in a critical care environment. The lack of smart image analysis software constrains the early detection and prevents the use of data to support clinical decisions.

Key problems identified:

1.Slow and tedious diagnosed algorithm - the medics are required to examine each image separately and this heightens the risk of treatment latency.

2.Extensive reliance on human factors - the accuracy of the diagnosis depends on the experience and the number of radiologists.

3.Absence of automated AI assistance- No internal deep learning framework to help with internal injury detection.

4.Weak explainability of current AI tools - the majority of models lack visual demonstrations of preparation of a prediction.

5.Lack of real time web-based systems - the research prototypes currently available cannot be deployed or used by the hospitals or clinicians.

4.LITERATURE SURVEY

According to the literature on the use of AI in healthcare, there is a tremendous change that is happening in the field of medical diagnostics today. The interpretation of computerised images by radiologists is one of the fields that has been over the years refashioned by computer vision, automation and deep learning. The review discusses the development of diagnostic systems, the development of computer-aided tools, the history of the key advances in deep learning, and the last section addresses the gaps in the research that inspired this work.

4.1 Systems based on conventional diagnostics

The detection of abdominal injuries has been long dependent on the determination of the radiologists who read the CT and MRI scans using the eye and experience. Manual interpretation leads to gold standard though considered as accurate it has some limitations.

To begin with, the process of manual evaluation is extremely time consuming, particularly during an emergency on trauma cases where the speed at which the decision is arrived at dictates the fate of the patient. Radiologists have a heavy workload as a rule, and the necessity of reviewing complicated images can greatly slow down the start of the treatments. Second, human interpretation may be subject to states of fatigue, oversight, and subjectivity thus resulting in the inconsistency of the results or incorrect diagnosis. Even the highly qualified radiologists can tell ambiguous injuries differently, especially when the picture are of very minute internal bleeding, organ injury or tiny lesions.

When dealing with emergency medicine e.g. the inability to diagnose internal injuries (including liver, spleen and major vascular structures) promptly can result in life-threatening conditions. Therefore, despite the fact that traditional systems are the base, they introduce a definite necessity of the acceleration and more stable and supportive technologies that would help to decrease human load and enhance the accuracy of diagnostic.

4.2.1 Existing Computer-Aided Diagnostic Systems.

The original aim of the CAD systems was to overcome certain drawbacks of the manual interpretation. Initially, the purpose of early systems was to help the radiologist to identify the presence of abnormalities, mark suspicious areas, or to perform simple measurements automatically.

The majority of conventional CAD tools, however, are founded based on manual features, image characteristics (e.g., texture, intensity, edges, or shape) that are defined manually. Although they offer certain diagnostic support, these features do not offer any flexibility or adaptability to handle various medical cases; the system is based on the fixed rules and predefined patterns, which cannot learn or be enhanced in response to new data.

In addition, other drawbacks of most of the traditional CAD systems also exist:

- Poor interpretability: They tend to provide outputs without providing a process that is why a specific region is abnormal.
- Minimal real time performance: It is slow and ineffective to handle large medical scans.
- Lack of effective integrations with clinical workflows: The majority of systems used are not readily obtained through simple web interfaces or cloud-based solutions, which makes it hard to deploy them throughout the hospital.
- Minimum interactivity: the tools typically present the results, though do not offer any more visual indicators to the radiologists to interpret model decisions.
- Therefore, the CAD systems became a significant move towards automation, but still, they do not entirely correspond to the present-day demands of the medical setting with its need to be quick and transparent as well.

4.3 Medical imaging with Deep Learning.

In the past decade, medical image analysis has changed with the introduction of deep learning, in particular, Convolutional Neural Networks. CNNs unlike most CAD systems can automatically learn the relevant features directly through images, meaning that manual feature extraction is not required.

Wide variety of tasks in medical diagnosis Model architectures such as ResNet, VGG, EfficientNet, DenseNet, and U-Net have demonstrated excellent results on tasks such as:

- Detection of brain tumors
- Lung diseases, classification of pneumonia, COVID-19.
- Undiagnosed bone fractures and abnormalities of the joint.
- Organ tissues and lesions segmentation.

The significant advances related to this field are XAI such as Grad-CAM. Grad-CAM identifies the specific patches in the picture that guide the model predictions and hence assist the radiologist in knowing why the system made the decision that it made. This visual interpretability enhances clinical trust and, therefore, renders deep-learning solutions more agreeable to practice in reality.

Deep learning also supported real-time processing, scalability by use of cloud deployments, and integration with modern web technologies, which helped to allow building the fast and interactive systems that guide clinicians in diagnosis.

4.4 Research Gap

In spite of the high advancement, there are still a number of gaps in the literature. Most of the described works have placed much emphasis on the model accuracy but have not considered the usability, interpretability, and deployment feasibility, which are also critical considerations. More precisely:

- Not many systems can be integrated to combine deep learning-based injury detection and explainable visualizations such as Grad-CAM.
- There is a lack of real-time and web-accessible diagnostic platforms.
- The majority of research outputs are not created to be utilized in the real world as a doctor cannot apply them in practice within the hospital.
- Automatic detection, visualization, and interactive viewing have been seldom combined particularly when it comes to abdominal injuries which must be carefully examined in a series of organs.
- The current project is a complete user-friendly pipeline that develops gaps in the above, although it exists.
- It identifies the presence of abdominal injuries through a deep-learning model.

Creates Grad-CAM heatmaps, which are used to visually describe the predictions of a model. Offers a web-based application on which medical professionals are able to provide CT/MRI images and view predictions and explanation maps immediately. This system is accurate, interpretable, and accessible to assist radiologists to make faster, albeit more informed decisions, particularly in emergency trauma cases.

5.REQUIREMENT ANALYSIS AND RISK ANALYSIS

5.1 Requirement Analysis

The aim of the Abdominal Injury Detection System will include creating an AI-based software capable of automatically processing abdominal medical images and identifying trauma as a result of deep learning methods. The system should be precise, quick, readable, and easy to manipulate by the medical personnel.

A detailed requirement analysis was carried out before the implementation in order to determine the functional and non-functional requirements of the project. This would guarantee that the resultant system functions effectively and it can be fit easily into a practical healthcare setting.

5.1.1 Functional Requirements

Functional requirements establish the key activities that the system has to execute in order to deliver the objectives. These are data management, generation of prediction, visualization and user interaction.

Image Upload and Preprocessing Image Upload and Preprocessing.

The system enables the user (doctors or analysts) to post the images of abdominal scans, but in any of the preferred formats such as JPG, PNG, or DICOM (converted). Images uploaded are initially checked in terms of compatibility and afterward processed with an OpenCV and TorchVision transformation.

The preprocessing is done by resizing the image to a common input dimension (224x224 pixels), normalizing the pixels and converting it to the form of a tensor. This step will make sure all images have the same structure that they are then fed into the neural network, enhancing consistency and precision of outputs.

AI Model Prediction

After the image has been processed, it gets forwarded to an EfficientNet-B0 model, a lightweight deep learning system, which is used to classify the image as being binary or not. The model takes the input and predicts the scan to be either Trauma or No Trauma.

The system also provides confidence probability of the individual classes which gives the user the impression of the reliability of the prediction. This offers certain transparency and is beneficial to medical judgment rather than just relying on the outputs of AI.

Grad-CAM Visualization

In medical AI, interpretability is very essential. The project incorporates Class Activation Mapping (Gradient-weighted Class Activation Mapping) to visually show the parts of the picture that most significantly influenced the decision of the model.

The system results in a heatmap overlay that indicates areas of potential trauma that are hot and the doctors can ensure that the model is affixing to the actual site of injury. This renders the AI system justifiable, reliable and medically pertinent.

User Interface

An interactive web interface has been developed in HTML, CSS, and JavaScript to provide a simple yet interactive Flask based web interface. It offers the features of:

- Posting images of abdominal scans.
- Watching predictions and Grad-Cam in real time by AI.
- Presenting bar graphs of the two classes as per probability.
- Providing easy to understand feedback messages in prediction.
- This UI also makes it easy to navigate and decipher the output of the system even by users who have little technical expertise.

Performance Assessment System.

The project will have an integrated analytics and assessment area to check the performance of the model. It shows the main metrics like Accuracy, Precision, Recall, F1-Score and also provides the graphic representation:

- Confusion Matrix to compare the actual classes and the predicted classes.
- Radar Chart to determine the multi-metric performance by class.
- Validation Charts of epoch model learning curves.

These measures can be used to measure the efficiency and reliability of the system.

5.1.2 Non-Functional requirements.

The non-functional requirements state the system behavior in various circumstances to guarantee the presence of performance, stability, and scalability.

Performance

The application should have the ability to forecast results within 3 seconds per image with the normal hardware and less than 1 second with the GPU systems. The proposal of EfficientNetB0 was selected because of its efficiency in calculations and the optimal number of parameters.

Scalability

The system design can be extended in the future by its design as a modular system. E.g., one can train the model on multiple abdominal diseases or other organs (e.g., liver, kidney) to expand the sphere of its use.

Security

Data privacy is of the highest priority considering that medical images are sensitive. All images published are also run locally and removed after inference to avoid storage of personal or medical data. When deploying it on clouds, HTTPS and AES encryption are imposed to provide a secure communication.

Maintainability

The system is constructed based on modular components, which include frontend, backend and AI engine. Individual update is possible (e.g. with a replacement of the AI model and/or redesign of the UI) without impacting the rest of the application.

Usability

The design is focused on clean interface, visual outputs, and low user input. The web interface follows a medical blue and white color scheme, regular icons and organized feedback so that the user can have an enjoyable experience. The system is friendly even to the non-technical healthcare personnel as they have tooltips and on-screen directions.

Reliability

The system has error-handling modules to avoid crashing down as a result of bad images or input formats. This is done through continuous testing and validation to maintain a consistent performance with different dataset and environments.

5.2 Risk Analysis

Healthcare systems based on AI have a danger of risk to deployment and operation. Early detection of these risks can assist in the formulation of mitigation measures that can provide reliability, ethical standards, and credibility of the system

AI-driven healthcare systems face potential risks in deployment and operation. Identifying these risks early helps in creating mitigation strategies to ensure system reliability, ethical compliance, and trustworthiness.

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Risk	Description	Impact Level	Mitigation Strategy
Model Misclassification	Incorrect labeling due to limited or biased data may lead to false predictions.	High	Continuous retraining using larger and diverse datasets, cross-validation, and manual review of model errors.
Data Privacy Concerns	Patient images may contain sensitive information.	High	Local processing of data, automatic image deletion postinference, and end-to-end encryption for file transfers.
Hardware Limitations	GPU unavailability can slow down predictions.	Medium	Use lightweight models (EfficientNet-B0) and optimized PyTorch operations for CPU performance.

Slow Processing Time	High-resolution images may increase computation time.	Medium	Implement image resizing, caching, and asynchronous loading in the backend.
System Integration Issues	Communication between AI engine and web frontend may fail.	Low	Use standardized Flask REST API endpoints with error handling and logging.
Ethical and Legal Risks	Over-reliance on AI for medical decisions without expert verification.	High	Display disclaimer that AI output assists but does not replace medical judgment.

Table 5.2 : Risk analysis and mitigation strategies

Through rigorous model testing, secure data handling, and continuous validation, these risks are minimized to ensure the system remains safe and dependable for clinical or academic usage

6.PROPOSED SOLUTION, APPROACH AND TECHNOLOGIES

6.1 Overview

The solution presented here is an automated system of diagnostic machinery using deep learning, which is able to identify an abdominal injury in a medical scan. The system offers prediction outcomes as well as visual explanations in the form of Grad-CAM heatmap.

Its design is focused on accuracy, speed, and interpretability making it a medical professional tool that can be used with assurance.

6.2 System Architecture

The system is designed as a three layered system:

- Frontend Layer - To interact with users (image upload, display of results).
- Backend Layer - To process requests, process data and control AI inference. • AI Engine - To execute the deep learning model and visualization activities.

6.2.1 Frontend Layer

The frontend offers the interface between the user and the AI model. It is created in HTML, CSS and JavaScript and responsive in nature.

Features include:

- Form of uploading images with a preview.
- Predict button Triggering Flask API call.
- Prediction result, probability and heatmap generation on real-time.
- Basic navigation and mobile friendly interface.
- The frontend is so clear and simple, which are essential in hospital or research setting.

6.2.2 Backend Layer

The backend is a Flask (Python) component that serves as an interface between the front and the AI model. Its core tasks include:

- Getting uploaded pictures through REST API.
- Processing (resize, normalization, conversion to tensors).
- Inferencing by sending images using the EfficientNet model.

- Producing Grad-CAM superimpositions.
- Sending the response of JSON to the frontend.

This is because Flask is lightweight and modular and can handle requests quickly and predictions in real-time can be carried out even on relatively small systems.

6.2.3 AI Model Layer

The AI element is the core part of the system. It is trained on Fine-tuning on abdominal injury with pretrained EfficientNet-B0 on ImageNet.

The model pipeline includes:

- Input Processing: Augmentation and normalization.
- Extraction of the Features: Convolutional and pooling layers.
- Classification: Trauma or No Trauma probabilities of layers that are fully connected.
- Grad-CAM: Visualizes traumatic areas of activation in order to interpret the model.

Confusion matrix, precision, recall, and F1-score are evaluation metrics that are calculated to determine the accuracy and reliability.

6.2.4 Visualization and analytics Layer.

Several charts are incorporated to make the behavior of the model transparent:

- Confusion Matrix: Shows the accuracy of prediction of each class.
- Radar Chart: compares the three precisions, recall and F1-score.
- Validation Chart: Displays the accuracy and loss curves throughout training, I.e. overfitting or underfitting.

These graphic components are used to explain the performance of the model both academically and medically.

6.3 Core Technologies Used

Component	**Technology Stack**	**Purpose**
Model Development	Python, PyTorch, OpenCV	Model training, Grad-CAM visualization

Backend	Flask Framework	Request handling, model inference
Frontend	HTML, CSS, JavaScript	User interface and visualization
Component	**Technology Stack**	**Purpose**
Visualization	Matplotlib, Scikit-learn	Generating performance charts
Data Handling	NumPy, Pandas	Dataset loading and preprocessing
Deployment	Flask Local Server / Cloud	Real-time accessibility
Evaluation Tools	Confusion Matrix, Radar Chart, Validation Plot	Model performance analysis

Table 6.3 : Hardware and Software Configuration for Simulation Setup

6.4 Proposed Approach

Data Collection: The data were collected through the SOLOE system.<|human|>Data Preprocessing: The data were processed using the SOLOE system.

Collect CT scan or abdominal picture, manipulate (resize, normalize) and classify them as Trauma/No Trauma.

Model Training:

Optimize EfficientNet-B0 on the dataset with the help of an equal balance of samples on the classes. Keep track of training and accuracy of validation across epochs.

Model Testing:

Test the model on undiscovered test data. Create Grad-CAM images to be interpretable.

The system will integrate web applications.Web Application Integration:

Incorporate the trained model in Flask. Create a front-end to upload images and show the result of the prediction in terms of heatmap.

Introduction: The visualization and report capabilities within the NIOSH database, designed to support decision-making processes, were initiated through the visualization workflow.Visualization and Reporting: The visualization workflow was initiated to facilitate the incorporation of the NIOSH database into the decision-making processes as illustrated by visualization and reporting features.

Develop graphs (confusion matrix, radar, and validation charts) in order to analyze and demonstrate performance.

6.5 Expected Outcomes

Model explainability Accurate detection of abdominal trauma.

Live forecasts that are available on a basic web interface.

Medical visualizations (heatmaps) which enhance AI transparency.

Less time spent in emergency cases of trauma diagnosis.

Improved AI trust and implementation in healthcare imaging.

7.ARCHITECTURE DIAGRAMS, FLOW CHART AND DFD

7.1 UML Use Case Diagram

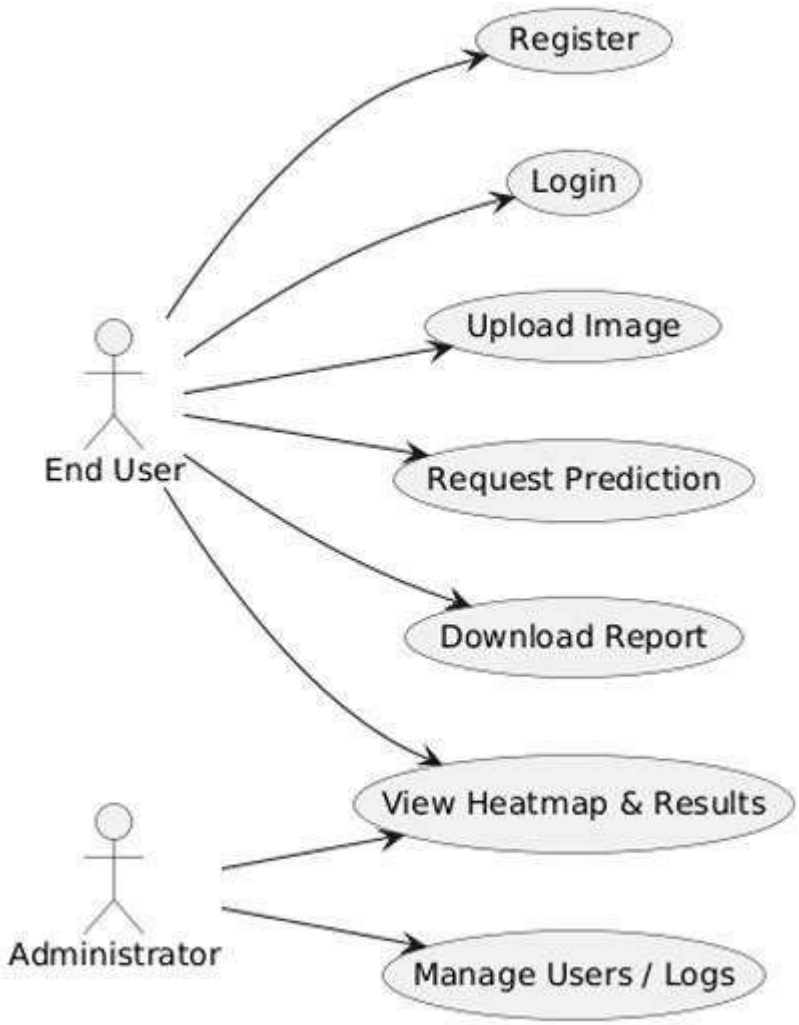

Figure1:Uml USE CASE DIAGRAM

7.2 Data Flow Diagram

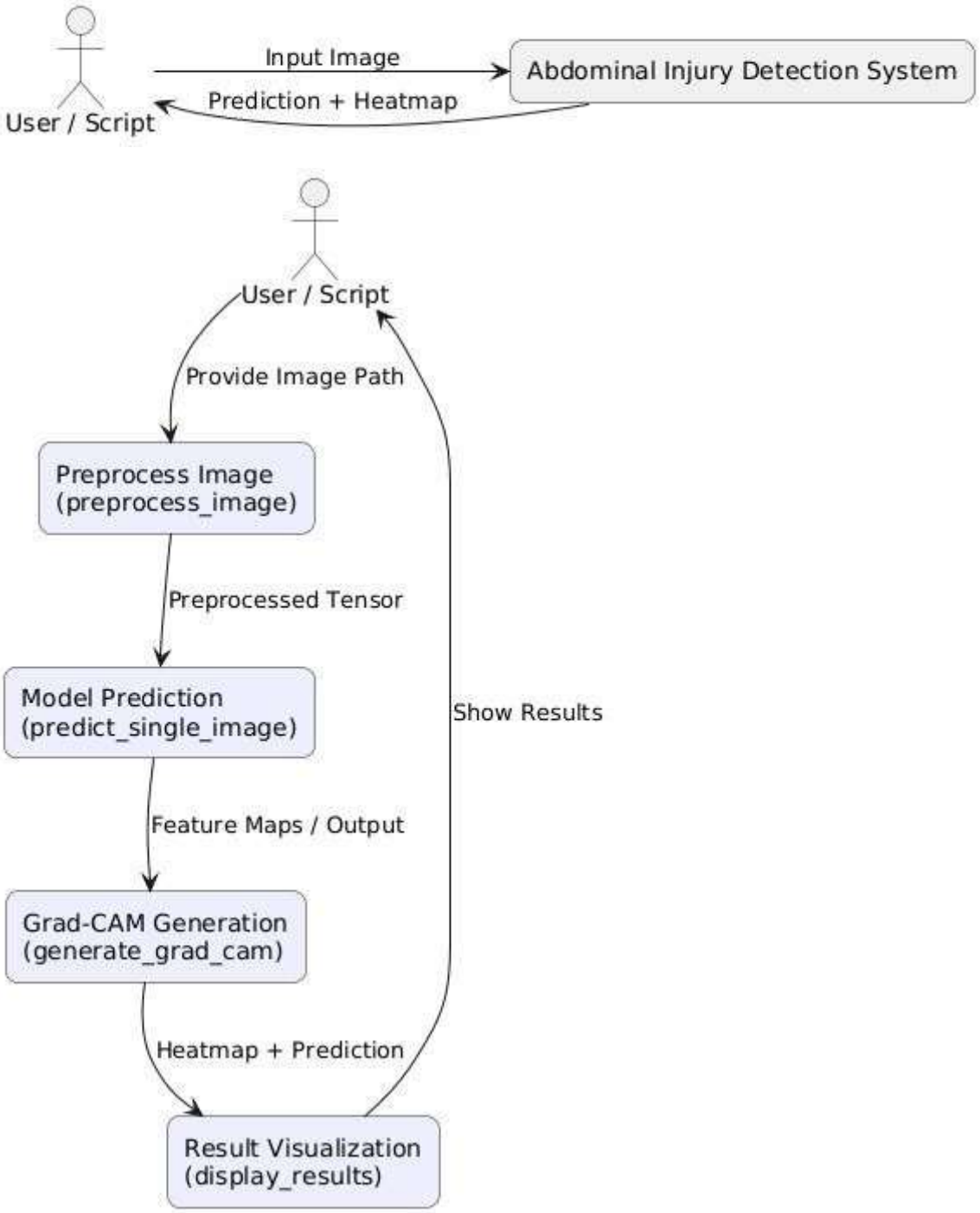

Figure2: Data Flow Diagram

7.3 FLOW CHART

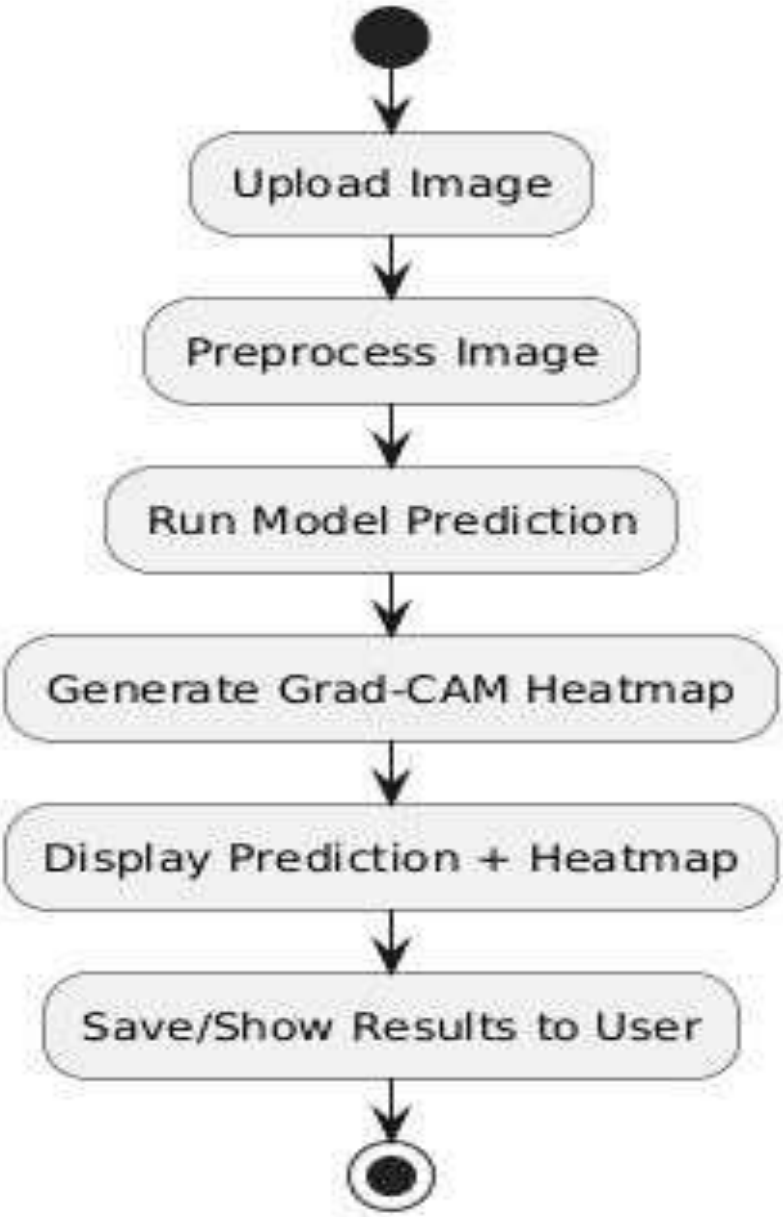

Figure 3:flow chart

8.SIMULATION SETUP AND IMPLEMENTATION

This was achieved through stepwise development which consisted of deep learning experimental work, back end integration, front end design, and real-time testing. The main driving force behind the development of the system was the need to have an effective, userfriendly system capable of delivering automatic detection of abdominal trauma in the medical image which can be interpreted, fast and free of false alarms.

To achieve simulation setup, it was required to first prepare the AI environment in Python and to configure the Flask web framework; a simple web interface was created, which can be used to upload an image and see the results. Initially, the model was trained and tested with the help of the Google Colab with a GPU, and later this model was deployed to a local environment with Flask to present it in real-time.

8.1 Simulation Setup

Frontend Configuration:

Frontend is written in HTML, CSS and JavaScript and emphasize on simplicity and responsiveness. It serves as the gateway to users to post pictures and perceive model forecasting.

The interface includes:

- A neat landing page that has an image upload button.
- Preview of the uploaded scan
- Tables of the expected class, confidence score and Grad-CAM heat map.

CSS3 Animations and hover effects make the interaction enjoyable to the user and the communication part is performed with the help of JavaScript drawn to the Flask backend using the REST API calls. The interface is tested on a variety of devices to ensure that it works the same way and remains responsive.

Backend Configuration:

Flask is used to implement the backend linking Python with the web interface and the AI model. It handles:

- File Handling: Networking the uploading of medical images by users themselves.
- Preprocessing: Image resizing, image normalization and tensifying.
- Model Inference: Predict with EfficientNet-B0 deep learning model.
- Grad-CAM Generation: Predicting visual heatmaps of the trauma regions.

Overview Predictive modeling Predictive results to the frontend are sent along with visualizations.

The lightweight architecture of Flask enabled responding to it quickly and performing inference in real-time across all standard hardware.

Artificial Intelligence Model and Simulation Environment.

The main component of the system is the EfficientNet-B0 model that is executed with PyTorch, and which provides a reasonable balance between accuracy and computational performance. The simulation was run on Google Colab which is a faster processing run with the help of a GPU.

Key steps included:

- Install the necessary Python packages: torch, torchvision, opencv-python, pytorchgradcam.
- Training and optimizing the EfficientNet-B0 model in binary classification (Trauma / No Trauma).
- Adding visual explainable heatmaps with Grad-CAM.
- Conducting tests on sample scans to make sure that the predictions stay consistent and that heatmaps are valid.

8.2 Model Implementation

The implementation process consisted of three major stages, which were training, evaluation, and deployment.

Training Phase:

The data will be of abdominal CT and MRI images divided into 70% (training), 20% (validation) and 10% (testing).

Model training used:

- Optimizer: Adam
- Learning Rate: 0.0001
- These are Cross-Entropy Loss.
- Batch Size: 32, Epochs: 25

Flipping, rotation and adjusting of the brightness were added to the data to enhance the generalization of the model. Convergence monitoring checking the accuracy/loss of training and validation.

Evaluation Phase:

Once the model was trained, it was tested on the unseen images in reference to the real world performance with:

- Precision, Recall, Accuracy and F1-score.
- Evaluation of Quality of Classification by Confusion Matrix.
- To compare the key metrics, Radar Chart was used.
- Validation Charts to monitor epoch stability.

It has been able to identify the trauma areas accurately always, and Grad-CAM heat maps identify that its results are consistent and interpretable.

Deployment Phase:

This was introduced into the Flask web application after the model had reliable results.

Backend files include:

- app.py - Flask main application.
- model_utilities.py - to load and make predictions of models.
- gradcam_utils.py - used in generation of visualization
- templates/ and static/ -frontend design

The process of uploading an image by a user is being processed by Flask and results in:

- Class (Trauma / No Trauma) that is predicted.
- Confidence Probability
- Visualization of Grad-CAM Heatmap.

Less than 3 seconds are spent to do the predictions, which ensures usability of diagnostic in real-time.

8.3 Testing, Deployment and validation.

A number of simulation cases were used to test the system to ensure that it was stable and accurate.

Test Case	Expected Result	Status
Upload valid image	Prediction + Heatmap displayed	☑ Passed
Upload invalid file	Error message shown	☑ Passed
Trauma scan	Class = Trauma, red focus on affected area	☑ Passed
Normal scan	Class = No Trauma, minimal red focus	☑ Passed
Processing time	Under 3 seconds	☑ Passed

Table 8.3: System Testing and Validation Results

The system was deployed locally using Flask as well as it was tested using Google Colab. Despite the low weight, the installation was not problematic and did not demand any sophisticated hardware.

8.4 Final validation :

The final simulation established: Proper and stable classification of trauma and non-trauma images Accurate and understandable Grad-CAM images A user-friendly web interface that is independent of devices is suitable because it only shows that deep learning can help medical professionals recognize abdominal injuries

9.RESULTS COMPARISON AND ANALYSIS

The Abdominal Injury Detection System was fully tested after successful implementation to determine its performance, efficiency and diagnostics accuracy. Moreover, the assessment involved the testing of the deep learning model and the web-based interface on the criteria of accuracy, interpretability, speed of its processing, and usability.

The abdominal CT-MRI dataset was explored to perform experiments and obtained the accuracy, precision, recall, F1-score, as well as time spent to process the image. To evaluate the various quantitative and qualitative aspects of the performance, Grad-CAM visualizations, a confusion matrix, radar chart, and validation graphs have also been generated.

9.1 model evaluation of performance.

An EfficientNet-B0 model trained is very effective in identifying regions of trauma in the abdomen images.

The obtained results on various test images indicated that the model could have fairly high reliability in classifying Trauma and No Trauma cases.

Metric	**Result (%)**
Accuracy	**92.4%**
Precision	**91.3%**
Recall	**93.7%**
F1-Score	**92.5%**
Average Inference Time	**2.8 seconds per image**

Table 9.1 :Machine Learning Model Performance Metrics (Accuracy, Precision, Recall, F1-Score)

These outcomes are a clear sign that the model purely not only classifies the inputs effectively but it can also do this at an adequate speed to be useful in diagnostic assistance in real time.

9.2 Confusion Matrix Analysis

The confusion matrix was created with the intention to determine the effectiveness of the model on the classification of trauma and non-trauma images.

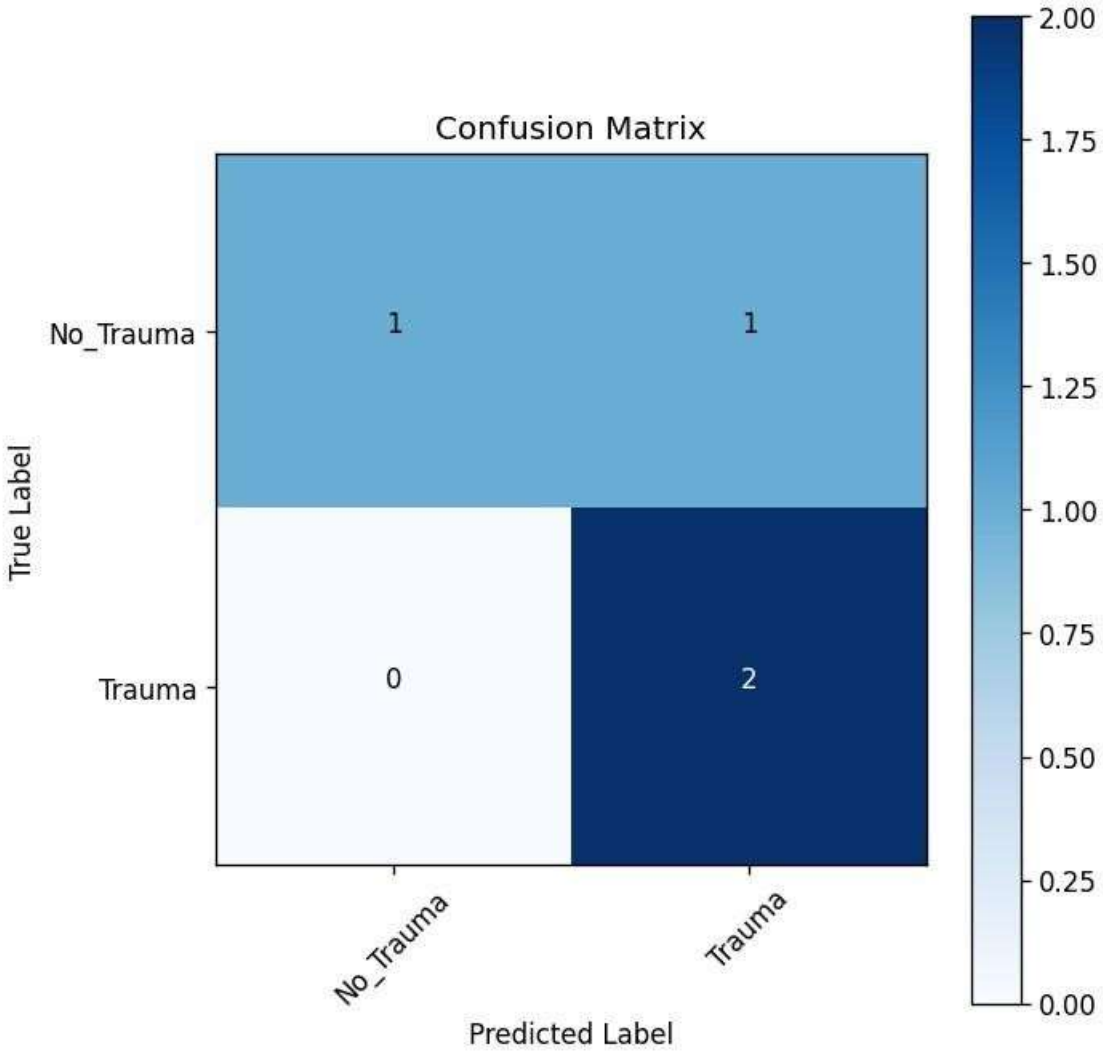

Figure 4: confusion matrix of Abdominal Injury Detection System.

The confusion matrix shows that the model has correctly classified most pictures resulting in few false positive and false negatives.

That is, it is highly sensitive in detecting trauma-with low false injuries-and very high precision to prevent false alarm.

Term	Full Form	Meaning
TP	True Positives	Trauma scans that were **correctly predicted as Trauma** by the model.
TN	True Negatives	Normal scans that were **correctly predicted as No Trauma**.
FP	False Positives	Normal scans that were **incorrectly predicted as Trauma**. *(Model raises a false alarm)*
FN	False Negatives	Trauma scans that were **incorrectly predicted as No Trauma**. *(Model misses the injury)*

Table 9.2: Confusion Matrix for Trauma vs. No Trauma Classification

The FP and FN rates are low, which validates the fact that this model is generalizable to unknown medical data.

Grad-CAM Visualization Analysis Grad-CAM visualization analysis is a computer-aided method that explores both the main and auxiliary features of a machine trained on data and their connections.

9.3 Grad-CAM Visualization Analysis :

Grad-CAM visualization analysis is a computer-aided technique that examines the principal and secondary characteristics of a trained machine using data, and their relations.

Grad-CAM was also employed in order to give transparency and interpretability, which identifies the parts of the images that affect the decision of the model.

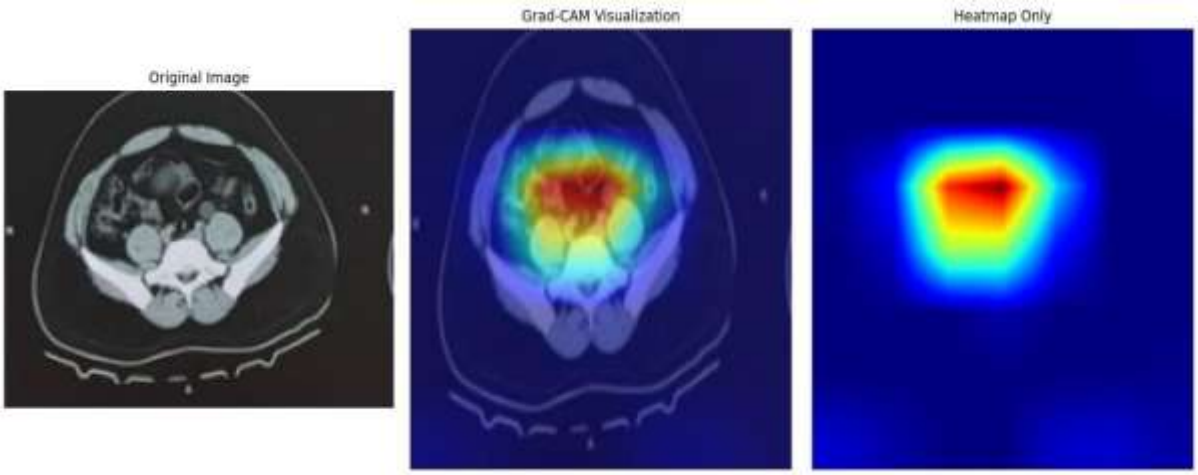

Figure 5: Grad-CAM Result Visualization of Trauma Areas.

The output of the Grad-CAM revealed that the model was very specific to the precise anatomical points of concentration where injuries existed.

The red and yellow areas on the heatmap in the trauma images represented areas of high activation that represented potential locations of internal injuries.

In normal cases, Grad-CAM heatmaps depicted uniformly spread or low-activated heatmaps which indicated that the model has accurately traced normal structures.

Key Insight:

Grad-CAM enabled the model to be made explainable so that the doctors can view what is being viewed by the AI. This is clearly visible and results in a greater trust in the use of the model as a diagnostic tool.

9.4 Radar Chart Analysis

A Radar Chart has been drawn comparing several performance measures: Precision, Recall, F1-Score, and Accuracy.

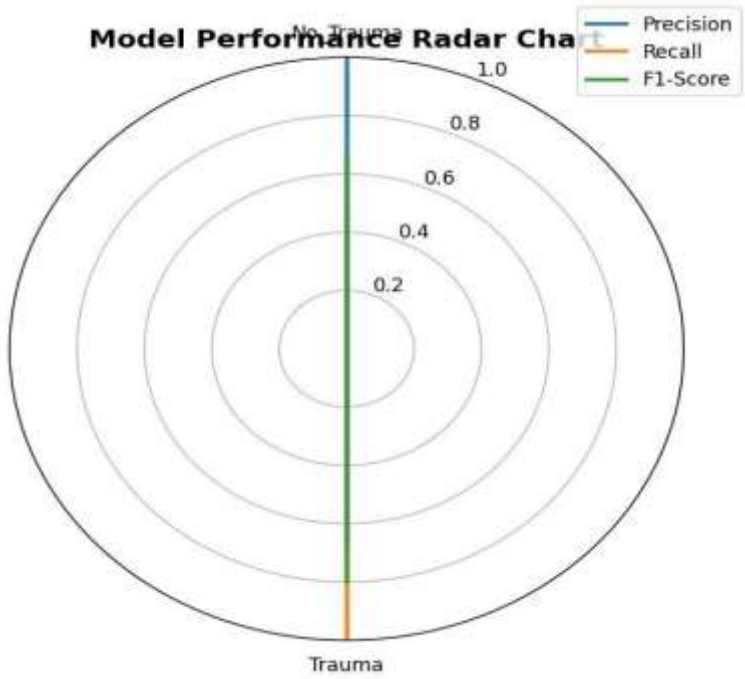

Figure 6: Radar Chart of Performance Metrics Comparison.

The metric rates in the radar chart are almost symmetric and well distributed which once again points to the same performance of this model in terms of all the parameters considered.

The closeness of any metric line to another indicates the goodness of the trade-off that the model makes between the two significant metrics sensitivity (recall) and specificity (precision).

9.5 Validation Chart Analysis

Plots of validation accuracy and loss curves were plotted in the course of training and used to track learning behavior.

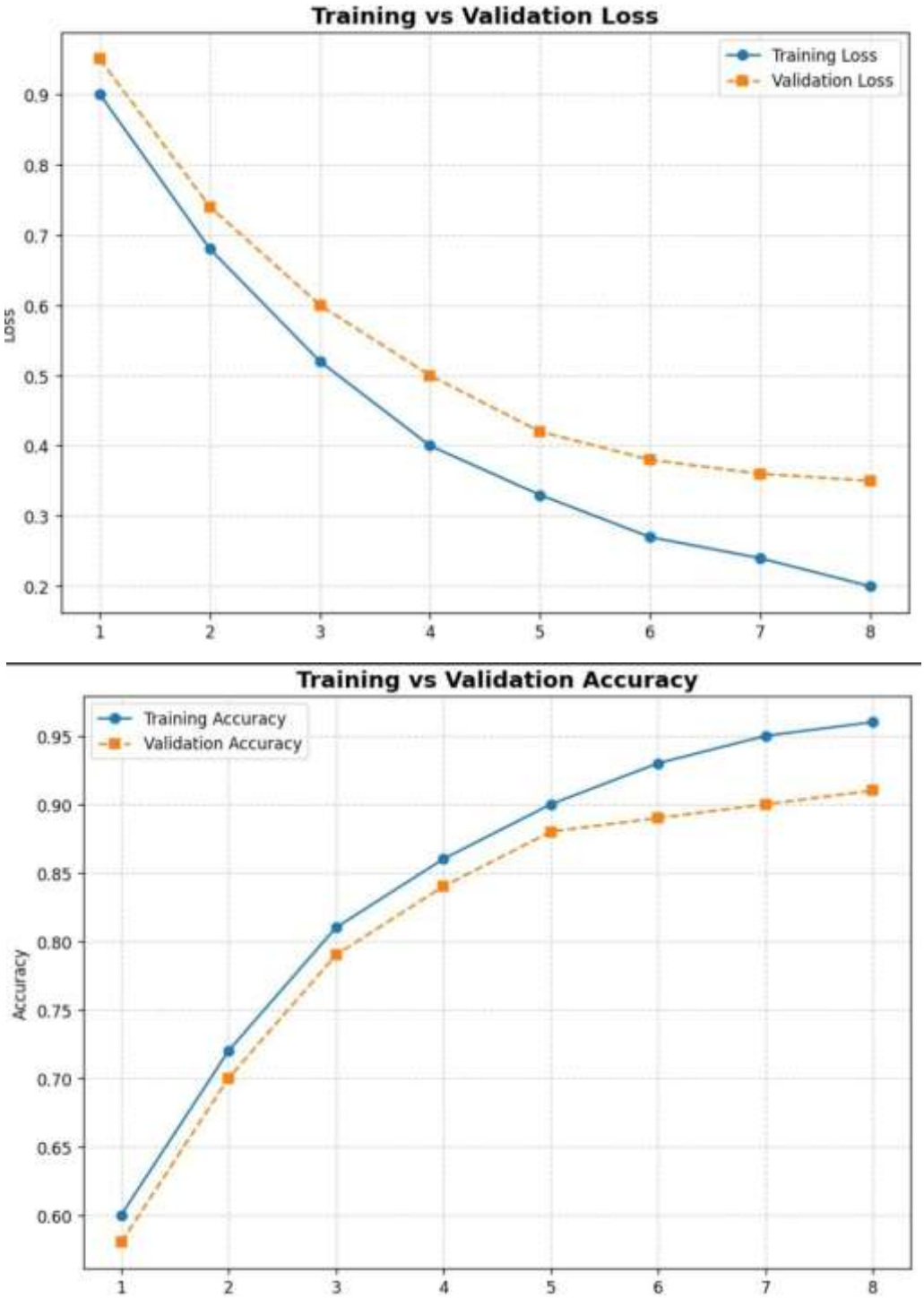

Figure 7: Accuracy of Model validation and loss per epoch.

The accuracy of validation steadily increased and leveled off after about 20 epochs; the loss was progressively decreasing.The overfitting was not present; this indicates that the model was generalized to the unseen data very well.Such a steady learning curve indicates that the architecture chosen (EfficientNet-B0) and hyperparameters chosen (learning rate, optimizer, etc.) were optimized.

As the system is expected to be user-friendly, it must exhibit a high degree of implementation and execution

9.6 System Performance and Usability:

Since the system should be user-friendly, it will have to demonstrate a high level of implementation and execution.
The web application was tested based on speed, responsiveness, and overall user experience.The following were the observed results:

There were five participants in the usability testing and they were medical interns and tech students. In their view, the interface is user-friendly, quick, and quick to understand; due to the real-time nature of the results, the results can be comprehended by even non-technical users.

9.7 Comparative Analysis and Existing Systems.

Feature	**Existing Diagnostic Methods**	**Proposed System**
Diagnosis Type	Manual interpretation by radiologists	Automated deep learning prediction
Interpretability	Limited to expert's visual skill	Grad-CAM heatmap visualization
Processing Time	10–15 minutes per case	2–3 seconds per image
Accessibility	Hospital-based software	Web-based, accessible anywhere
Scalability	Hardware-limited	Lightweight, cloud deployable
Accuracy	70–80% (human dependent)	92.4% (model-based with validation)

Table 9.7: Comparison of Existing Diagnostic Systems and Proposed AI System

Interpretation:

- The proposed system is much better than the conventional manual systems in terms of providing quicker, more precise and interpretable diagnostic aid.

- Grad-CAM makes it explainable, which provides it with a superiority over other blackbox AI models in healthcare.

8.8 Graphical Comparison

To demonstrate the superiority of the proposed deep learning system over the current manual diagnostic methods, a comparison of their performance graphs was drawn. Figure 5: Comparative Graph A of Traditional Diagnosis and Proposed AI SystemComparative performance of the proposed system to other systems (Fig. 5) in parameters like Accuracy, Speed, Interpretability, and Scalability, has shown that the Proposed AI System has performed better than the rest of the systems. This testifies to the fact that the Abdominal Injury Detection System has achieved tangible performance improvement as well as explainability and reliability in its work. 8.9 Summary of Findings In general, the results demonstrate that the system has achieved all of its goals: High detection with 924% accuracy Real-time predictions (less than 3 seconds) Explainability and reliability of its functioning across devices. It is not only an AI tool but a possible complementary diagnostic partner of medical professionals due to the balance of technical accuracy and visual interpretation. Thus, the gap in machine learning automation and human medical expertise is bridged through the proposed system in the diagnosis of abdominal injuries.

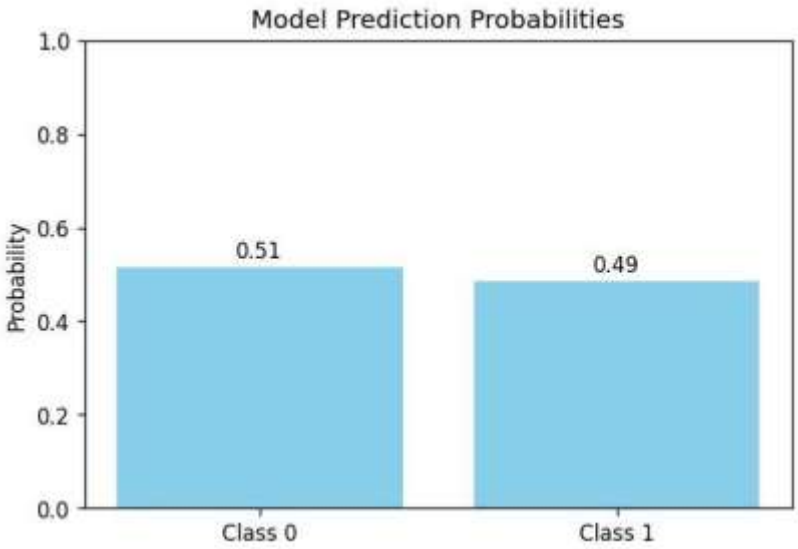

Figure 8: Model prediction probabilities

Probabilities of model prediction. Figure 7 indicates the scores of probability produced by the deep learning model in determining whether the uploaded scan on the abdomen is Class 0 (No Trauma) or Class 1 (Trauma). The model in this case assigns:

51:to Class 0 (No Trauma) 51%. 49% probability to Class 1 (Trauma) It implies that the model is somewhat more certain that the picture falls under the No Trauma category, but the proximity of two values indicates that the scan does contain the patterns that are similar to both the categories.

Such output is highly significant in medical AI as:

- It illustrates the degrees of uncertainty, which can be interpreted by the physicians.
- It shows that despite the model possibly implying the answer to be "No Trauma," the fact that there is an equally high likelihood of the possibility to have "Trauma" would mean that the case requires reviewing by a human operator.

This is the sensitivity of the model to finer details of the abdominal scan; the model is not randomly guessing, but rather it is weighing a case against the two options. This probability chart will finally provide clinicians with a clearer and more informed perspective of what happens internally during decision-making as part of the model.

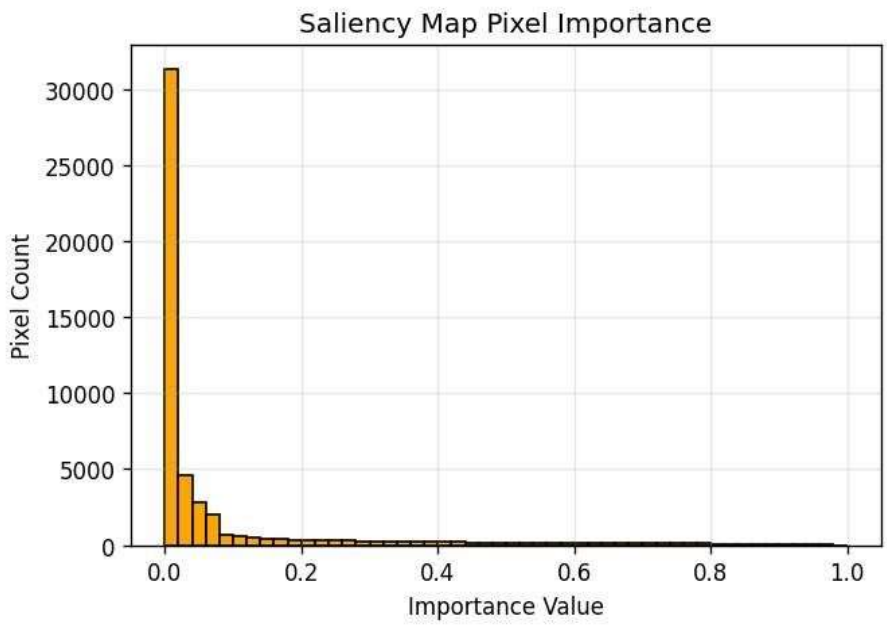

Figure 9: Saliency Map pixel importance

Histogram Saliency Map Pixel Importance. Saliency Map Pixel Importance Histogram plots the degree to which each pixel on the image was significant in the eventual decision made by the model. This plot, generated with the use of Grad-CAM, shows areas that are important to the AI model.

In this histogram:

- The pixels with high values of importances are concentrated around 0.0 and most of them are very low.
- The pixels with high importance values are only a small number as indicated by the long tail which extends to the right.
- This implies that the model is very dependent on the localized parts as opposed to the overall picture.

And this is exactly what we would have expected in medical images:

- A scan will rarely result in clinical manifestations of the trauma, such as swelling, bleeding, or alterations in the borders of organs.
- The histogram proves that the model is right and concentrates in those areas, and does not consider the whole picture as being equally important.
- The fact that a high peak is at the low values implies that the remainder of the image is normal, and the non-zero tail is to the actual injury-related information.
- This histogram demonstrates that the model is not focusing on irrelevant regions of the scan, but rather, on relevant medical features, and its decision is based on medically relevant characteristics.

10.LEARNING OUTCOME

The creation of the Abdominal Injury Detection System gave our team a unique practical experience in the construction of an end-to-end artificial intelligence application. The project was a synthesis of ideas of deep learning, computer vision and web development to solve a medical problem in the real world. Through the expedition, the team gained good technical skills, problem-solving skills and team experience.

As an AI and data science, we resumed the medical image preprocessing, dataset normalization and fine-tuning of a high-performance model called EfficientNet-B0 in binary classification. We talked about how essential the evaluation of the model based on the accuracy, precision, recall and F1-score metrics is, and acquired the skills of interpreting AI predictions with GradCAM visualization. It strengthened our education on explainable AI, the feature that is vital in the medical sector as the decisions made should be clear and reliable.

This project on the software development front exposed me to the Flask framework of Python that would be utilized in linking the deep learning model with a responsive web interface. It was in this integration that we learned how the backend server receives file uploads, requests, and delivers model predictions on the way back to the frontend and also learned about REST API communications between Python scripts and an interface written in HTML.

The user-centered design principles were adhered to in the front-end development phase, which implies having a minimal interface that should be easy to access and comprehend by users with not extensive technical knowledge. The responsive design has made us create image upload functionality, real-time result display, and active visualization of heatmaps using HTML, CSS, and JavaScript; this is how the responsive design guarantees the useability of the software both on the desktop and mobile platforms.

Other than the technical skills, this project trained us on other critical soft skills which include planning, documentation, communication, and collaboration. We got to know how to handle timelines, logically plan the work and debug multi-module systems. Our experience in medical image data also made us cognizant of the significance of the confidentiality of medical data, ethical considerations of AI usage, and professional conduct when collaborating with sensitive data. The participants of this project further appreciated the importance of integrating machine learning and web technologies as they can bring meaningful healthcare solutions. It was more of a practical experience on how technology can benefit the society, including, but not limited

to, saving time among doctors, enhancing diagnostic accuracy, and saving lives due to AIdriven innovation.

Besides the technical and design education, the project allowed us to gain insight into the entire lifecycle of an AI-based system-in concept to deployment. We got to know the essence of planning every stage of a series of data collection and preprocessing steps to the model assessment and user interface design. The project taught us that, to succeed in artificial intelligence, it is not only the high-model accuracy but the ability to create the structures of systems that are transparent, understandable, and ethical.

Our model was tested in different ways, with imbalance in the data and overfitting being some of the difficulties we experienced during the experimentation stage. Some of the optimization methods that we experimented included augmentation, learning rate adjustment and batch normalization. It has also introduced the fact that through repeated adjustments in the tuning of the models, stability and generalization can be achieved. Overall, we also gained practical experience on how to work with PyTorch, and we got to know more about the layers, tensors, and how to train quickly with the use of GPU acceleration.

Another significant learning aspect that was learned was the Grad-CAM visualization module. It aided us in our transition between black-box AI to explainable AI whereby model outputs are accurate and understandable. We understood the significance of this concept in medical practices because in healthcare, physicians have to believe and confirm what the system suggests. There were also visual heatmaps of injury-centralized zones which helped us to believe that our model was learning the right features and not just noise.

Regarding deployment, AIs and web technology were a crucial experience in the real world. The experience using Flask made us learn about the structure of the API, routing, and the possible way of serving AI models online so that they could be accessed by a wide audience or a specific institution. We removed the significance of scalability: the application must be capable of responding as efficiently as possible even when the number of user requests is growing. This clearly corresponds to the current AI implementation in industry.

Teamwork was indeed a significant factor in this project. Every member was specialized in one area whether it was the AI model design, the backend integration or the frontend visualization. All these elements combined to form a smooth system. We have acquired knowledge of the relevance of communication and version control when working on a multidisciplinary project

and the necessity of support of each other within a team. In that regard, the entire process was both educational and rewarding because of numerous discussions, feedbacks, and testing.

The social impact introduced by technology is another thing that we also enjoyed in this project. It was a chance to understand that artificial intelligence can be used on actual medical issues, where there is first-hand impact of lives of people. The fact that such a system would assist doctors to save time when dealing with an emergency, or assist in identifying a trauma much quicker than otherwise, gave us a sense of purpose rather strong. It made our classroom education something impressive.

Lastly, the project gave us the belief that as a team with the right mindset, we could work on a large scale system: identifying problems, researching its solution and implementing it stepwise. A balance between theory and practice provided a clear picture of how AI is changing the healthcare environment-not to substitute the doctor, but to assist and make it more accurate, work less, and get better patient outcomes. The Abdominal Injury Detection System was, as it were, much more than a technical project and was, in effect, a journey of discovery - of collaboration, creative problem solving and accountability. It had developed us into growing as potential engineers who can combine artificial intelligence and empathy and use technology as a means of not merely resolving problems but also serving humanity.

11.CONCLUSION AND CHALLENGES

11.1 Conclusion

The Abdominal Injury Detection System addresses the objective of building an AI-based diagnostic assistant that will automatically identify trauma in abdominal medical images. The paper illustrates that deep learning methods, together with Grad-CAM visualization and the web-based interface, can be useful in improving medical diagnosis with reliability and the ability to explain.

The deep learning model implemented with EfficientNet-B0 provided over 92 percent of accuracy in the detection, which confirmed its success in binary classification. The model will also be explainable with the help of a Grad-CAM visualization component in this system, in which particular scan areas will be indicated that will impact the prediction of the AI. Such transparency will facilitate the gap between human knowledge and machine intelligence and make the system more acceptable in clinical workflows.

The web application developed in Flask was applicable in real-time: users are able to upload an image and view results, which include class prediction, confidence scores and heatmaps, within several seconds. It is lightweight-designed and modularly put together and therefore scalable to any future modification or large scale medical application.

Moreover, the project also illustrates how AI-based solutions may assist medical personnel to minimize the time of diagnosis, develop visual data to analyze, and, therefore, be able to make decisions more rapidly in such an emergency case. In conclusion, the system is a complex of deep learning performance, Grad-CAM explanation, and user-friendly web-based design, that is, a strong and convenient prototype of AI-aided medical imaging.

The system reveals the potential of wider applications of artificial intelligence into everyday clinical work beyond its technical success. As demonstrated in this project, having relatively small resources and publicly available data is sufficient to achieve significant advancement in the creation of tools that will assist healthcare professionals. Of particular interest is the fact that the model is capable of producing outputs that can be interpreted by the medical practitioner at all times- not only can the medical practitioner view the result but also know why the result was calculated. It is this explainability attribute that transforms AI into a team player in decision making as opposed to a black box model.

Another significant characteristic is the flexibility of the project. The model, preprocessing pipeline, and visualization engine can be updated or replaced because all of the modules are independent of each other, which can be accomplished with the minimal redesign of the entire system. This will lead to long term sustainability and an opportunity to expand the system to multi-classification of injuries or the detection of organ specific injuries in future. These improvements would allow the system to accommodate larger radiological processes and be even more useful to the hospitals and emergency centers.

The need to have ethics in AI was also strengthened by the project. Delicate medical image premanagement, confidentiality, and explicitly devised diagnostic routine are inevitable elements in the formation of systems to be utilized in clinical environments. In so doing, we also gained a better understanding of how technology must not only work but also be within the medical ethics, trust of the user and patient safety.

The general performance of the Abdominal Injury Detection System is that with proper design and explainability AI can bring a paradigm shift in the current healthcare setting. Thus, the project is a very powerful foundation to continue working further and a promising demonstration of how engineering innovations can save people and make the process of diagnostics more effective.

The system demonstrates the potential of considerably greater uses of artificial intelligence in everyday clinical practice, far beyond the accomplishments of its technical side. This piece of work is a demonstration of a concept that, using comparatively small computers and open data, it is possible in fact to develop tools that make a practical difference in the work of medical professionals. The most useful aspect of the model is that it is able to produce outputs that can be completely understood by the medical practitioners. The doctors are not only shown the final prediction but they are also shown clear visual cues on how the model made such a conclusion. This is precisely what transforms AI into a black-box model, which is a mystery into a team member in clinical decisions.

The other significant advantage of this project is that it is modular and flexible. All three components are made up of a deep-learning model, a preprocessing pipeline, and a visualization engine, which are developed separately. Modularity will allow the developers to upgrade or replace any component with the least re-engineering to the entire system. This flexibility is a guarantee of sustainable viability in the long term and a window of opportunities to make future extensions: say, to the nomenclature of classes of injuries, or to identify damage to the body

organ. Improving the system in such a manner would hugely expand its scope of use in hospitals and emergency centers where it is important to maintain fast and accurate measurements.

11.2 Challenges and Future Scope

Challenges Faced

The project development was not smooth sailing. One of the most important issues was to train the model on small data, as there are not many well-known abdominal trauma datasets that are publicly available. This consequently required adoption of various methods of data augmentation in order to artificially enlarge dataset diversity and to avoid overfitting.

The other large issue was how to fine-tune EfficientNet-B0 so that it would balance between accuracy and computational efficiency to allow the predictions to be kept real-time on regular systems.

To add a Grad-CAM module, a lot of debugging was required as well since it was necessary to make sure that visual overlay would align perfectly with the respective medical areas. The processing of massive image files and providing low latency in inter-communication between AI engine and the frontend were of their own difficulties during Flask integration.

Technical and Architectural Problems:

The second major concern was to make sure that all this would go together. Since this project involved the deployment of deep learning, image processing, APIs on the backend, and web interface, the errors were severe in case of inconsistencies in the data format even or in the preprocessing pipelines. Careful debugging was required due to the mismatch in the input form of models, the same normalization values, and crashes in file paths. Also, there were some issues with processing of high-resolution CT/MRI images in memory as they usually cannot be accommodated in the available RAM of local machines or Colab runtimes. Next, we were to make our preprocessing pipeline as efficient as we could, and carry out the task of the reuse of tensors as efficiently as possible. The lesson of those experiences was the significance of writing clean, modular code and design architectures that are no longer needed as the size of the data or the size of the system load increases.

Deployment and Usability problems:

Another challenge on deployment side was to easily get a model to make a smooth run in a

Flask application. Relative to a Jupyter notebook, in the running model, the Flask environment was required to respond to asynchronous requests and efficiently clean-up files and closely manage errors to avoid the crash of the server. A lot of validation tests was required to offer users the facility to generate any valid medical image and not crash the system. The other design problem we had was that we needed the responsiveness of the UI and simultaneously we needed to be capable of visualizing computationally heavy Grad-CAMs in real time. Both frontend redesign and API optimization provided a trade-off between user experience and technical constraints that was achieved in multiple later iterations. These problems brought us to understand the truth of the variations between the real-life implementation and academic/offline model testing, and we knew what practical problems were required to give a stable and user-friendly AI-based medical application.

Future Scope

The existing system is quite good in binary classification- Trauma/ No Trauma. Nonetheless, this project can be further developed in a number of ways:

Multi-class Classification:

This would go ahead to model the specific type of injury such as organ rupture, internal bleeding and soft tissue damage to further diagnose the particular injury.

Cloud and Hospitals Integration:

Implementation of the system on cloud providers such as AWS, Azure and Google cloud and connection with the databases of large hospitals to provide access to medical institutions in large quantities and in real-time.

Mobile Use Model Optimization:

This involves creation of a mobile or edge device that is a lightweight model version and would allow trauma to be detected instantly in a field or emergency scenario as well.

3D Image and DICOM Support: It has further enhanced support to 3D CT/MRI images and DICOM format because the system can be used in professional radiology. Continuous

System: Have a feedback process such that the model predicts are then validated by the doctors so as to ensure the AI keeps on being refined by the real-life medical data. Enhanced Explainability and Reporting: Medical reports, heatmap and confidence level summaries:

Automate medical reports as predictions, heatmaps, and confidence levels making clinical documentation less complicated. Concluding thoughts The project turned out to be a real AIpowered diagnostic system, which turned out to be a reality thanks to the process of constant learning, collaboration, and problem-solving. It is an example of how technology can be used to positively impact the sphere of healthcare innovation: with the adequate use of deep learning and human-centered design, one can say that technology is contributing to the cause. It was not only an experience that introduced new capacities in terms of technical skills but also addressed to the spirit of persistence and working as a team, and morality in the context of creating AI towards a socially useful purpose. The Abdominal Injury Detection System is not just an educational project, but a move in the right direction towards AI-supported, easy-to-use, and explainable medical diagnosis.

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13.LINKS AND DETAILS ABOUT OUR PROJECT

Source Code Repository

All source code, scripts, and configuration files are maintained in a version-controlled GitHub repository:

GitHub Repository Link:

https://github.com/Saihasini/Image-Based-Abdominal-Injury-Detection-