Real-Time Joint Bleeding Detection and Clinical Decision Support System for Hemophilia Patient

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FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements forthe **Degree of Bachelor of Science in Computer Science and Engineering**

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APPROVAL

This Project titled **"Real-Time Joint Bleeding Detection and Clinical Decision Support System for Hemophilia Patient"**, submitted by Dipto Chaccroboti, ID No: **213-15-4321** to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **16 September, 2025.**

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DECLARATION

We hereby declare that this project has been done by me under the supervision of **Mr. Md. Sazzadur Ahamed, Assistant Professor**, Department of Computer Science and Engineering, Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

Hemophilia is a rare genetic bleeding disorder where blood does not clot properly due to lack of clotting factors, Factor VIII in Hemophilia A and Factor IX in Hemophilia B, which can result in spontaneous and recurrent internal bleeding, particularly into joint spaces such as knees, ankles, and elbows. If not treated quickly, joint bleeding can lead to pain and swelling, and eventually joint damage. In Bangladesh, most patients experience prohibitive delay in clinical evaluation, including travel to referral centers. This paper presents a Novel Real-Time Joint Bleeding Detection and Clinical Decision Support Tool for the Remote Assessment of Hemophilia-A patient's joint. Through the Regional Youth Committee, a dataset of more than 2000 images of joint bleeding has been collected across the country with the approval of Hemophilia Society of Bangladesh. After Augmentation in Roboflow the image increase to 5000 Certified hemophilia specialists categorized the images into five classes: severe, moderate, mild, fixed joint, and no bleeding. Different deep learning models including CNN with Xception and hybrid model ViTForImageClassification with DenseNet121 were trained. The highest validation accuracy attained was 81.82% with unedited images, underscoring the significance of background context in the medical image classification process. The best-performing model was saved as an .h5 file and this was used to develop a web application with Flask. Using this system, patients are able to receive on-the-go assessments and treatment recommendations from doctors in real-time, enabling timely action and reducing.

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Chapter 1

Introduction

This chapter provides an overview of the research, including the background, problem statement, motivation, objectives, methodology, expected outcomes, and the overall structure of the report.

1.1 Introduction

Hemophilia is a rare genetic disorder where blood doesn't clot properly, causing excessive bleeding. Two type of Hemophilia- Hemophilia A (lack of factor VII), Hemophilia B (lack of factor IX) [1]. This condition results in internal as well as external bleeding episodes and is certainly more complex than people realize. An ever-present challenge for individuals living with hemophilia is the risk of bleeding into the joints, most often the knees, ankles, and elbows [1]. Without intervention, these injuries not only restrict movement, they also inflict constant pain and may disable the individual. For patients residing in rural or far-off locations, there is a critical shortage of real-time clinical evaluations in Bangladesh. The majority of hemophilia patients have to wait in long lines and travel vast distances to see specialists in cities like Dhaka, which adds a financial as well as logistical burden to the already lengthy treatment process. This project attempts to address the problem of early and comprehensive detection and management of joint bleeding by creating a real-time image-based classification and clinical decision support system.

Figure 1.1: Joint Bleeding symptoms (Knee, Ankle, Elbow)

1.2 Motivation

The motivation for this project comes from both computational and humanitarian angles. From a technological standpoint, it is possible to apply deep learning and computer vision in real medical cases, which is a very appealing opportunity. On a personal level, the motivation is strengthened by the inequalities in clinical access in Bangladesh faced by hemophilia patients. In particular, this system can improve their remote self-assessment capabilities, which helps diminish suffering, prevent enduring complications, and improve the patient's control over their own health. There is also the possibility to make a difference in the emerging area of AI in healthcare, especially in underfunded areas which makes this project very appealing. At the individual level, motivation is supported by the differences in clinical access among the hemophilia patients in Bangladesh. Most of the patients are rural and have to travel long distances, sometimes to Dhaka, to meet a specialist, which is expensive and dangerous during emergencies. This system will alleviate some of that load by allowing patients to remotely monitor their joint bleeding status by simply uploading images. This could be used to reduce suffering, avoid chronic complications, and allow patients to have more control over their health.

1.3 Objectives

The main objectives of this project are as follows:

1. To gather and develop a dataset of joint bleeding images from hemophilia patients throughout Bangladesh.
2. To define five clinically important categories of joint bleeding: severe, moderate, mild, fixed joint, and no bleeding.
3. To develop and implement deep learning algorithms which classify joint bleeding conditions from images with high accuracy.
4. To get the effect instant medical feedback based on real-time bleeding condition.
5. To create an .h5 model and implement the model into a real-time web application using Huggingface.ai.

1.4 Methodology

Image collection for the project commenced with gathering 2,000 joint bleeding images from patients in different districts of Bangladesh, enabled through the Regional Youth Committee (RYC) and the Hemophilia Society of Bangladesh.

Roboflow was used to perform image augmentation to improve model generalization and increase dataset size, which resulted in an additional 5,000 images. Each original image was augmented three times using the following transformations:

- Horizontal Flip
- Rotation (90° both clockwise and counter-clockwise)
- Crop Zoom (Minimum 0 %, Max 20%)
- Brightness change (dimming or brightening from -15% to +15%)

Along with expert annotation into five categories, several deep learning models were developed and evaluated, including CNNs with Xception and a hybrid model with (ViTForImageClassification)Vit and DenseNet121. The effects of background removal from images on the model performance was also analyzed. The model with the best results was saved in .h5 format which allowed it to be utilized in a web application built on Flask for automated joint bleeding detection and real-time support decision making by and for patients.

1.5 Project Outcome

The project will achieve the following key goals:

1. Generation of a labeled dataset consisting of 2,000 original and 5,000 augmented images of joint bleeding.
2. Computation of comparative deep learning model analysis with a maximum validation accuracy of 81.82%.
3. Understanding the effect of the background context on classification performance.
4. A working real-time deployable .h5 model.
5. Real-time web application prototype for patient-reported joint bleeding assessment and care guidance.

From the perspective of the patient:

1. Through the mobile or web application system, patients can assess the severity of their joint bleeding by snapping a photo of the affected area.
2. Automated feedback informs the user whether the issue can be resolved at home or needs to be addressed at the hospital which helps in curbing unnecessary visits and delays to treatment.

3. Assists in prompt clinical judgment by automatically suggesting appropriate Factor dosage based on classified bleeding severity level (per clinical protocols).

4. The system minimizes the time gap between symptom occurrence and professional assessment for patients residing in rural regions thus protecting the patients from permanent joint damage.

1.6 Organization of the Report

This report has six chapters that sequentially represent the development of the real-time bleeding detection and clinical decision support system of hemophilia patients in its entirety.

Chapter 1 should be an introduction of the project which contains such items as background of the hemophilia, difficulties with joint bleeding in patients, motivation to address this issue, project objectives, the methodology the project chose to follow, what the project is likely to give and finally the structure of the report at large.

Chapter 2 portrays the background and the context of the study. It consists of a literature review of the current research and technologies dealing with hemophilia management, specifically with machine learning and clinical support tools. In the chapter, there is also a gap analysis where it is noted that there is no image-based joint bleeding detection systems available in real-time in Bangladesh and the world at large.

Chapter 3 describes research methodology and design of the system. It encompasses the data preparation which is composed of collecting the data used on the patient data across Bangladesh and the augmentation of data with Roboflow. Model selection, system architecture, functional and non-functional requirements, context and data flow diagrams, UI design, project plan, and task allocation are also described with the help of this chapter.

Chapter 4 explains how the project is implemented, setting up a machine learning environment, testing the model performance, and comparing accuracy pre- and post-background removal as well as how the last model is built into a web app that is based on Flask. The outcomes are scrutinized to find out the strategy that offered the highest level of validation accuracy.

In **chapter 5**, the standards and ethics of engineering are considered. It talks about compliance of software, social and environmental impact possibility, sustainability and the way the system will facilitate access to healthcare of marginalized patients. It is also a commentary on how difficult can the process of curing a dire health condition be when employing AI and software technologies.

Chapter 6 is the conclusion of the report, which states all the work in a brief summary, provides its limits and gives future improvement, which may be presenting mobile apps, or use ultrasound data in enhancing and so on.

Chapter 2
Background

This chapter outlines the scope and significance of this research. It contains a literature review, pertinent technologies and datasets, an evaluation of analogous applications, as well as the short description of the research gap that this project seeks to fill.

2.1 Introduction

Hemophilia is an uncommon type of bleeding disorder characterized by insufficient clotting factors, particularly Factor VIII and XI [1]. Among the most prevalent and hazardous complications of hemophilia is joint bleeding (hemarthrosis) which, when left untreated, may result in chronic pain, irreversible damage, and disability to the joints. Even in countries like Bangladesh, which face a lack of resources, patients have to struggle with accessing timely diagnostic and therapeutic services, particularly in the rural regions [1]. This investigation seeks to aid hemophilia patients in real-time detection of joint bleeding using image-based classification with deep learning algorithms, enhancing the precision and accessibility of early diagnosis. According to World Federation of Hemophilia (WFH) updated report there are total 400,000 up hemophilia patients identified around the world [8]. In Bangladesh according to Hemophilia Society of Bangladesh database total 4000 up registered hemophilia patient found [5]. But They faced lots of problem to get service or treatment care as well.

2.2 Literature Review

A number of investigations have studied the clinical history, complications, and management protocols of Hemophilia. In this area, emerging technologies like AI and image processing are beginning to make an impact, albeit in a limited capacity. The literature reviewed is summarized in Table 2.1.

Clinically and data driven, the reviewed literature gives an exhaustive click on how hemophilia is understood. The treatment guidelines and classification standards presented globally by Srivastava et al. [1] have been accepted as the valid ones. Multiple investigations were dedicated to Bangladesh consumption Islam et al. [2] and [3] reviewed clinical patterns, complications, and demographic tendencies of hemophilia and hemophilia carriers mainly among children. Karim & Jamal [4] provided more comprehensive clinical information on the cases of pediatric hemophilia. Chaccroboti et al. [5] also provided useful information about the situation of hemophilia in Bangladesh, providing a dataset containing how many Hemophilia A and B patients are present in the country classified by the severity of the disease and geographical locations in an excel table. Gooding et al. [6] also regulated the significance of detecting joint bleeding at an early stage by analyzing biomarkers, whereas Tyrrell et al. [7] also showed how AI helps detect hemarthrosis via ultrasonography. Finally, Coffin et al. [8] presented worldwide data obtained on a huge patient registry, where trends were observed in over 10 000 hemophilia patients. All these studies coupled together form a very robust basis towards designing AI-based decision support tools that would satisfy the needs of both stakes at the local and global levels. A. Bohr and K. Memarzadeh [9] provide a guideline to take factor injection during bleeding situation. Another paper suggests a hybrid deep learning architecture that fuses DenseNet, Vision Transformer (ViT) with an attention fusion mechanism to enhance the accuracy and redundancy of EEG-based epilepsy seizure prediction [10].

Table 2.1: Summary of Literature Reviewed.

Author (s)	**Year**	**Title**	**Methodology**	**Key Findings**
Srivastava et al. [1].	2013	Guidelines for the Management of Hemophilia	Clinical review	Defined comprehensive treatment guidelines and severity classifications.
Islam et al. [2]	2022	Clinical Profile of Hemophilia Patients in Bangladesh	Observational study	Highlighted demographic patterns and access limitations for treatment.
Islam et al. [3]	2016	Hemophilia in Children	Pediatric study	Focused on complications and case outcomes in Bangladeshi children.
Karim & Jamal [4]	-	A Review on Hemophilia in Children	Review article	Outlined general and clinical perspectives on hemophilia cases.

Chaccroboti et al. [5]	2024	HemoData Dataset for Hemophilia Diagnosis	Dataset publication (Mendeley)	Provided a dataset of hemophilia images to aid in diagnosis and AI research.
Gooding et al. [6]	2021	Asymptomatic Joint Bleeding in Hemophilia	Review & biomarkers analysis	Discussed early indicators of joint bleeding and the need for timely detection.
Tyrrell et al. [7]	2024	AI Detection of Hemarthrosis Via Ultrasonography	AI-assisted ultrasonography (CNN / ResNet)	Demonstrated AI use for identifying bleeding in joints using imaging tools.
Coffin et al. [8]	2023	World Federation Bleeding Disorder Registry	Global data analysis	Shared insights from over 10,000 hemophilia patients across the globe.
A. Bohr and K. Memarzadeh [9]	2020	The rise of artificial intelligence in healthcare applications	Clinical review	Provide a guideline to take factor injection during bleeding situation.
S. Yuan et al [10]	2014	EEG-Based Seizure Prediction Using Hybrid DenseNet–ViT Network with Attention Fusion	Vit + DenseNet	Attention fusion and a hybrid DenseNetViT model enhance the prediction of epilepsy seizures by EEG.

2.2.1 Similar Applications

Detection of joint bleeding in hemophilia patients using mobile or web-based AI tools is still emerging. Diagostic ultrasonography and MRI are not accessible in low-resource settings. Tyrrell et al. [7] used AI and ultrasonography, but it needs clinical infrastructure. Databases such as the World Bleeding Disorders Registry [8] compile patient records on a global scale, but their purpose is not for real-time diagnosis. In Bangladesh, my project is one of the pioneering attempts in the country aimed at developing a real-time joint bleeding detection system using images and classification.

2.3 Gap Analysis

The comparison shows that proposed system makes a step forward compared to the current system explained by Tyrrell et al. [7]. The reference system applies artificial intelligence to diagnose hemarthrosis with point-of-care ultrasonography, although it lacks real-time bleeding in the joint based on images, accessibility by mobile phones, or serving low-resource or rural patients. It also does not provide guidance on urgency of treatment and factor dosage, not trained on local data of Bangladesh patients, and has no web-based interface on emergency consultation. The proposed system, in contrast, solves all these constraints and provides real-time bleeding detection based on images, mobile and web access, locally trained models, and clinical decision support to enhance the timely and accessible care of hemophilia patients in Bangladesh. This proposed system is not only useable to improving life of hemophilia in Bangladesh but also it would be play a great role all around the world.

Based on the literature and available technologies, the following Table 2.3 gaps have been identified that this project aims to address:

Table 2.3: Gap Analysis.

Features	**Existing Systems [7]**	**Proposed System**
Real-time joint bleeding detection from image	No	Yes
Smartphone/mobile app accessibility	No	Yes
Support for low-resource/rural patients	Limited	Yes
Suggestion for treatment urgency and dosage	No	Yes
Locally trained with Bangladesh-based patient data	No	Yes
Web-based emergency interface for remote consultation	No	Yes

2.1 Summary

In the first parts of this chapter, the history of the clinical presence of hemophilia, as well as the technological milieu of the diagnostic systems, was presented. Although different imaging techniques have been effectively used and artificial intelligence tools have been implemented in medical diagnosis to pick up bleeding, there has been a severe lack of imaging based real-time diagnostic tools that are outfitted specifically to the intra-articular bleeding in patients with hemophilia. This is an acute problem in low-resource environments, where special equipment and imaging as well as professional assessment are limited. The examined sources help underline the discussed gap in that despite the availability of some useful clinical data and means to detect it, the majority of those approaches center around clinic tests, ultrasound, or other, in general, medical imaging that may not be applied in the clinical setting by the direct hands of patients. In response, the current study uses locally generated data of Bangladesh to develop a web-based system with AI-assisted capabilities and features to be mobile-friendly to offer a cost effective and accurate, user tuned diagnostic assistant to healthcare providers and the patients.

Chapter 3
Research Methodology

This section describes the design, methodology, and planning involved in creating the real-time bleeding detection system for hemophilia patients. It consists of system architecture, design choices, specifications of requirements and criteria, as well as work decomposition.

3.1 Methodology/Requirement Analysis & Design Specification

3.1.1 Overview

In this project, I want to create a clinical decision support tool to determine the conditions of bleeding in the joints of hemophilia patients by classifying the image using deep learning. Joint bleed, especially knee, ankle, and elbow are patients of concern who have hemophilia whether they live in a low-resources country like Bangladesh or elsewhere. To deal with this problem, joint bleeding will be classified into five levels, which are Severe, Moderate, Mild, Fixed Joint, and No bleeding, depending on visual cues related to swelling, pain, temperature, and joint mobility. A collection of 2,000 actual joint images was obtained in the whole country with the help of the Regional Youth Committee (RYC) upon authorization by the Hemophilia Society of Bangladesh. The images was augmented to 5000 images by performing augmentation techniques of flipping, rotating, adjusting brightness, and zoom aims of making the model have a better generalization capacity. The architectures tested include DenseNet121, Xception and a convolutional backbone image embedding pipeline, which uses a Vision Transformer (ViT). The architecture that produced the best validation accuracy was ViT Enrobing, DenseNet121 with a 81.82 validation accuracy. It is worth noting that the comparison of the model trained with the background removal and the model trained without it was performed, offering insights into the influence of the preprocessing procedure on clinical image classification.

To be deployed, rather than hosting a traditional solution based on Flask, the model was first transformed to a .h5 file and incorporated into a web application hosted by Hugging

Face, which has a more cloud-friendly interface in terms of real-time prediction. It is a platform that will enable patients and caregivers to take the images of joints and use them directly to report their condition via a mobile or Web device, which provides immediate assessment regarding the severity of their bleeding. Python is used as the backbone of the project and TensorFlow and PyTorch as the deep learning frameworks to train and test the models.

This solution will allow decentralized real-time clinical diagnosis that can vastly cut down on cases of unnecessary hospitalization and help to make better decisions regarding the right time to make interventions faster and have modern patients and doctors make informed decisions remotely.

3.1.2 Proposed Methodology

In below figure (fig: 3.1) shows that the proposed methodology will start with the identification of the problem, which is the joint bleeding analysis in real-time among hemophilia patients. Once the project plan had been prepared, it was checked and confirmed with the Hemophilia Society of Bangladesh and then the requirements were gathered directly by interviewing the patients. The next stage involved the data collection carried out by Regional Youth Committees (RYC) throughout Bangladesh, which led to 2,000 joint bleeding images belonging to five categories: severe, moderate, mild, fixed joint and no bleeding.

In order to improve the dataset, 5,000 samples were added to the dataset by augmenting with Roboflow, which included flipping, rotation, cropping, and brightness adjustments. Even the model training was done on the prepared dataset consisting of varying CNN and hybrid models. Precisely, they consisted of Xception (with background), DenseNet121 (without background), and hybrid networks based on CNN and ViT embeddings under background and non-background data.

The highest validation accuracy was obtained in the best-performing model (ViT + DenseNet121 with background). Lastly, the model was trained as a web-based application with Hugging Space to deploy the trained model using the .h5 model file to make it available to hemophilia patient and caregivers in real-time. This figure 3.1.2 shows the overall methodology of this research as well

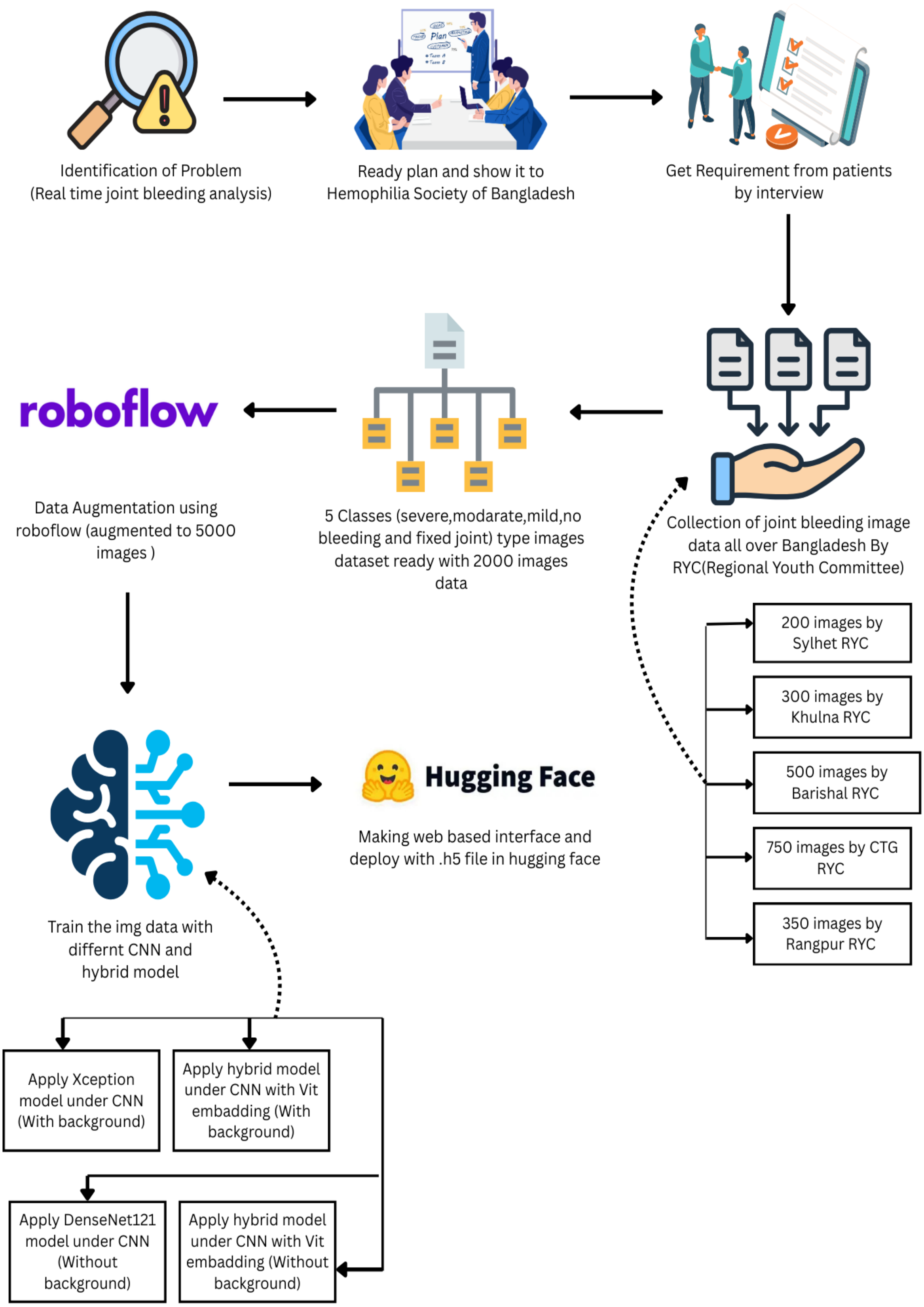

Figure 3.1: Methodology flow diagram

3.1.3 Functional and Nonfunctional Requirements

Functional Requirements:

1. Upload joint bleeding images via web interface.
2. Classify images into five categories: Severe, Moderate, Mild, Fixed Joint, No Bleeding.
3. Used ViT + DenseNet121 hybrid model trained with original (non-background-removed) images.
4. Compare different model performances during evaluation:
   - CNN (Xception)
   - ViT + DenseNet121 with background
   - ViT + DenseNet121 without background (tested but not used)
5. Display prediction result with suggested action (home care or hospital + factor dose).
6. Integrate pre-trained .h5 model via Hugging Face web platform.
7. Maintain patient data privacy.

Nonfunctional Requirements:

1. Fast prediction (<5 seconds).
2. Web Based application for user friendly UI.
3. Minimum 80% model accuracy target.
4. Simple and intuitive UI.
5. Secure and private image handling.
6. Compatible with major browsers and devices.
7. Easy to maintain and update.
8. Scalable for multiple user access.

3.1.4 UI Design

In below figure:3.1.1 showing that the web interface pages of real time joint bleeding detection which deployed with hugging face web-based hosting platform as well. Here you can see the image input option to user can easily upload images and click image in real time and upload here.

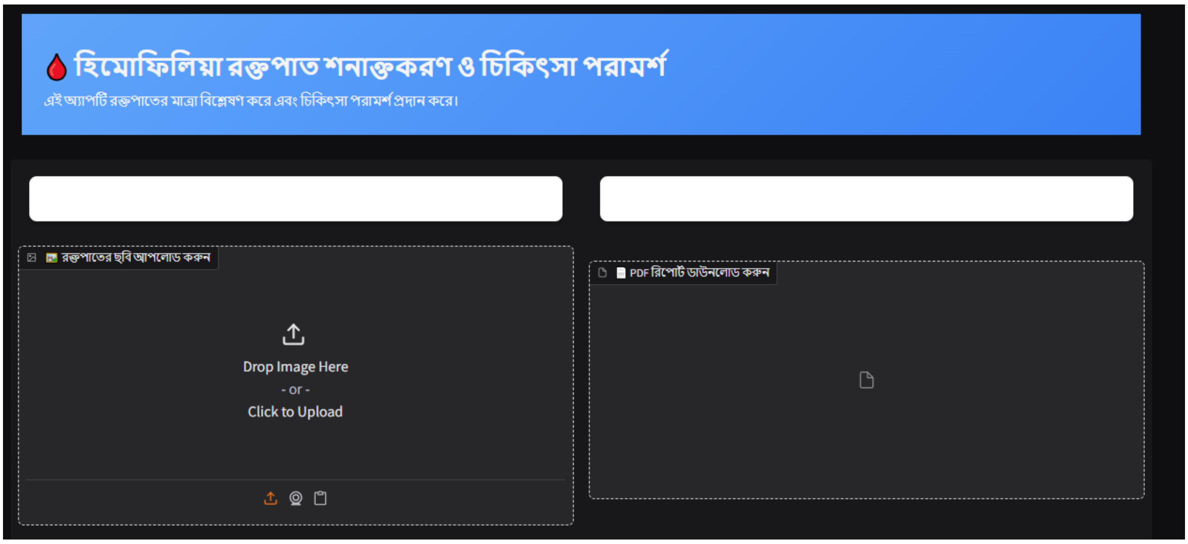

Figure: 3.1.1: User Interface of joint bleeding detection

In below figure:3.1.2 showing some things then there are some questions which needed to calculate factor injection doges as well. User need to input the joint pain, fever situation, age and weight as well.

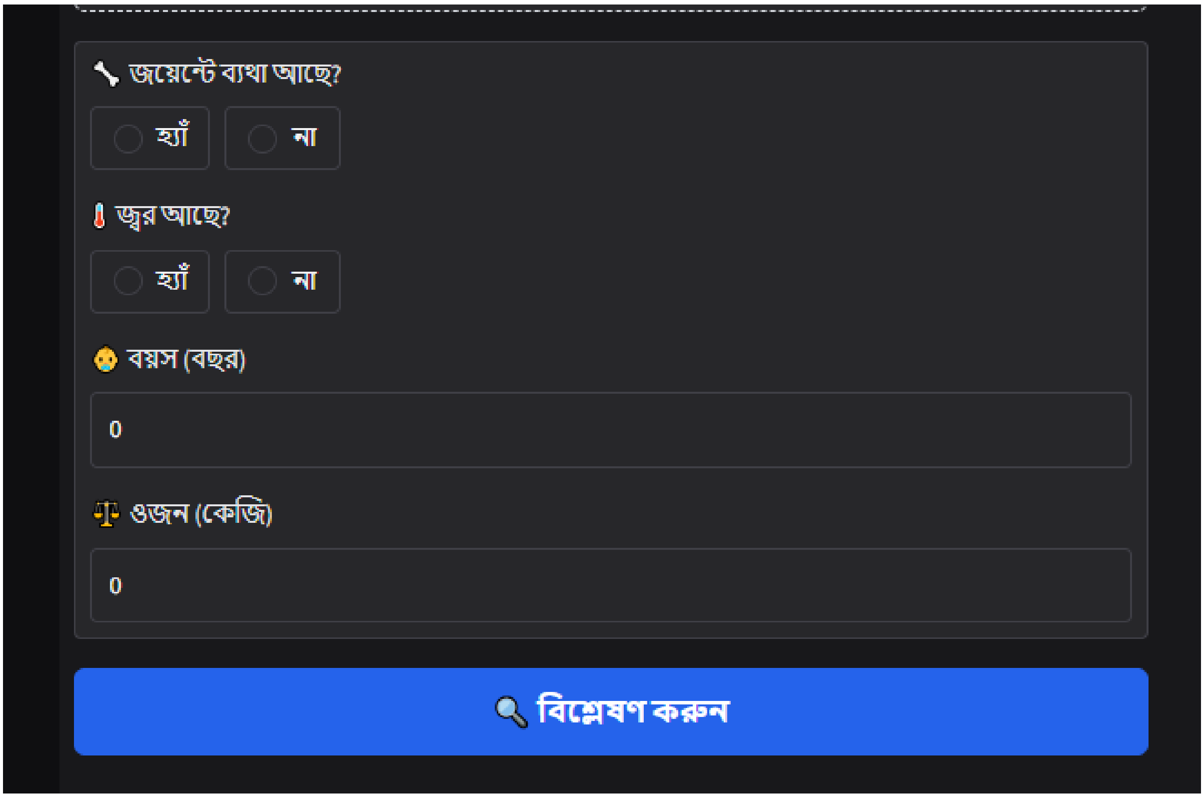

Figure: 3.1.2: User Interface input basic info

In below figure:3.1.3 represent the result of detection bleeding condition as well.

When user upload bleeding image and submit this question (Age, weight, fever, pain) and our model predict the severity of bleeding and suggested them for next treatment to cure from this condition or prevent of bleeding.

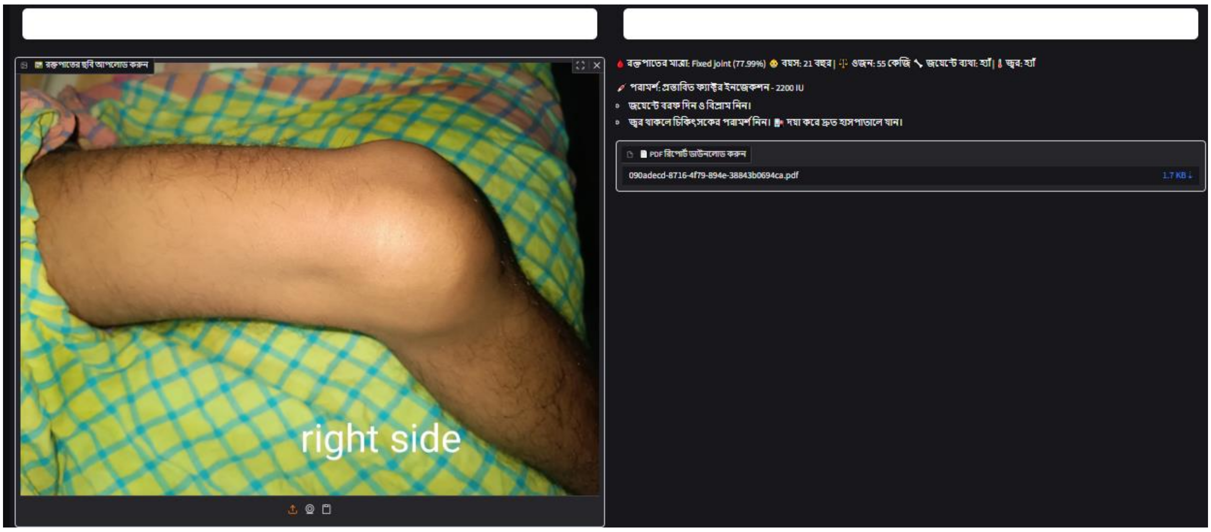

Figure: 3.1.3: User Interface of joint bleeding detection report and result

3.2 Detailed Methodology and Design

The systematic workflow of the detailed methodology of this project was to ascertain technical accuracy as well as clinical relevance. All the steps of the process are presented below:

1.Identification of Problem: The initial step was to define the clinical issue that the hemophilia patients were experiencing, specifically the absence of real-time devices to measure the severity of joint bleeding. The reason why this problem is selected is that joint bleeding is a common and grave complication of hemophilia, but most patients in Bangladesh are not able to access specialists or diagnostic centers easily.

2.Planning and Consultation: A project plan had been made and was submitted to the Hemophilia Society of Bangladesh to review. Their permission and response were a guarantee that the system met actual patient requirements. Also, patients were interviewed to collect their requirements and refined the scope of the problem and identified the five classes of bleeding, namely, severe, moderate, mild, fixed joint, and no bleeding.

3.Data Collection: Joint bleeding images were gathered in various districts around the country with the assistance of Regional Youth Committees (RYC) of Hemophilia Society of Bangladesh. Two thousand images were collected; 200 images were taken in Sylhet, 300 images were taken in Khulna, 500 pictures were taken in Barishal, 750 pictures were taken in Chattogram, and 350 pictures were taken in Rangpur. These pictures were the main dataset used in training a model.

Fig:3.2 (Images Data)

4.Data Augmentation: Since the first set of data was very limited, the image data size was augmented from 2,000 to 5,000 by employing data augmentation practices provided by Roboflow. Augmentation included horizontal flipping, 90° rotations, random cropping and variations of brightness to form a wide variety of the original images. This made the dataset more enriched, varied, and reduced the risk of overfitting to the model.

5.Model Training and Comparison: The expanded data set was then applied to train and test several deep learning devices. we had Xception, and DenseNet121, among other models, alongside hybrid architectures that combined CNN with Vision Transformer (ViT) embeddings. Background-preserved and background-removed images were trained and tested to quantify the changes in performance. The best performing model is the hybrid ViT + DenseNet121 consisting of background images which produced a validation accuracy of 81.82%.

6.Deployment: The best model obtained during training was saved in. h5 format and served through Hugging Face Spaces. This deployment offered a user-friendly web interface for patients and caregivers to upload joint images where immediate predictions are reported back. Thus, it operates as a decision support system with implications in real time, to allow early identification and better handling of bleeding episodes.

Alternative Methods Considered:

1. **Xception**: Lightweight, gave initial baseline performance (~64%)
2. **DenseNet121**: Performed better with pre-trained embeddings
3. **ViT (Vision Transformer)**: Helped in extracting stronger features
4. **Background Removal**: Initially tried to improve accuracy but led to a drop to 74.31%

Final Decision:

The best results were obtained with **ViTForImageClassification + DenseNet121 hybride model**, which maintained ~81.82% validation accuracy without removing object background as well. This combination was selected for deployment.

3.3 Project Plan

The below Table 3.3 shows the project plan to complete the research and deploying the web interface public.

Table 3.3: Project plan update table.

Task	Duration	Status
Data Collection	5 weeks	Completed
Data Augmentation	1 week	Completed
Model Training	2 weeks	Completed
Background Removal Experiment	2 weeks	Completed
Deployment web application	2 weeks	Completed
Final Testing	1 week	Pending…

3.1 Task Allocation

Given that this is a solo project, one team member managed and completed all the core tasks. These tasks encompassed planning, data preparation, model creation, backend integration, and drafting the report. Nonetheless, during the data collection stage, the members of Regional Youth Committee (RYC) of Hemophilia Society of Bangladesh contributed greatly by collecting images of joint bleeding from various districts across the country.

Table 3.4: Task Allocation table

Tasks	Weeks																	
	12	14	16	18	20	22	24	26	28	30	32	34	36	38	40	42	44	46	48
Data collection phase																			
Data Preprocessing																			
Image Augmentation																			
Model Training & Tuning.																			
Performance Evaluation																			
Deployment (Hugging Face).																			
UI Design & Web Interface																			
Report Writing																			

3.1 Summary

This chapter illustrated the system design framework, methodology and development of the hemophilia joint bleeding detection system. It identified the requirement analysis, proposed architecture, the functional requirements and non-functional requirements and UI considerations. The methodology in detail consisted of data collection, augmentation, strategy of experimentation in the model, and evaluation strategies. Dozens of deep learning models were trained in order to determine the most accurate and efficient architecture to use in the real world. The emphasis was on the development of the solution not just that is precise but that is also available, quick, and intuitive to people in the Bangladesh health care sector as well as the patients. The deployment model with Hugging Face Spaces will have the benefit and aspect of making the system lightweight and provided as a web interface, thereby becoming an effective tool to aid clinicians.

Chapter 4

Implementation and Results

This chapter is devoted to implementation of joint bleeding severity classification system. It reports the technical configurations, model training, and comparison of the results, and the insights they carried.

4.1 Environment Setup

All of the models were trained in Kaggle Notebooks which offered free, GPU capable environment that was optimal to perform deep learning task. We chose Kaggle due to its flexibility, the ability to work with massive amounts of data, etc. Also, it can be readily connected to Python and the most recognizable ML libraries:

- **Platform**: Kaggle notebooks (runs on GPU T4 X 2)
- **Programming Language:** Python 3.10

Frameworks and Libraries:

- **Deep Learning:** TensorFlow, PyTorch
- **Data Handling & Preprocessing:** NumPy, Pandas, OpenCV
- **Visualization & Analysis:** Matplotlib, Seaborn
- **Model Deployment:** Hugging Face Spaces
- **Data Augmentation:** Roboflow (External Platform)

Dataset:
The original images of hemophilia-affected joints numbering 2,000 were gathered with the assistance of the Regional Youth Committee (RYC), Hemophilia Society of Bangladesh.

Data Augmentation: Roboflow (External resource)

- **Horizontal Flip**
- **90° Rotation**
- **Zoom Crop (0%–20%)**
- **Brightness Adjustment (±15%)**

Hardware: DCL laptop (Core i3 processor)

4.2 Comparative Analysis

A number of deep learning architectures were implemented to classify bleeding on joints into Severe, Moderate, Mild, Fixed Joint, and No Bleeding. To determine the different impacts of performance, models were tested with and without the background removal as well. This table 4.2.1 shows the result accuracy of my trained models.

Table 4.2.1 Models Comparison table

Model Setup	Img Background	Validation Accuracy
Xception (Basic CNN)	Present	65.00%
ViT + DenseNet121 (Feature Embedding)	Present	**81.82%**
DenseNet121	Removed	60.00%
ViT + DenseNet121 (Feature Embedding)	Removed	74.31%

Observations:

1. The most effective solution was a hybrid one with image embedding using Vision Transformer (ViT) and classification on DenseNet121.
2. Background removal tended to reduce accuracy most of the time probably because valuable visual information like joint discoloring or swelling are also lost.
3. Xception was somewhat okay and did not give off fine-tuned sensitivity as the ViT-enhanced models.

This table 4.2.2 Comparative Analysis between *"Utilizing Artificial Intelligence for the Detection of Hemarthrosis in Hemophilia Using Point-of-Care Ultrasonography"* [7] by Tyrrell et al. (2024) and my research.

Table 4.2.2: Comparison between one similar system

Tyrrell et al. (2024)	My Research
Ultrasound images of joints	Normal RGB images of joints
CNN / ResNet	ViT + DenseNet121

Not specified	81.82%
Deployment in Hospital imaging systems	Deployment in Web app via Hugging Face Spaces for everyone use to detect their joint bleeding condition

The similarity brings out one of the basic methodological differences between the two studies. Tyrrell et al. (2024) applied ultrasound imaging, which has specific equipment and personnel with special training, so in the field it is better on the territory of hospitals. Conversely, the study is dependent on the normal RGB images of a joint, which can be recorded with any smartphone camera, which means that the method is likely to be more affordable in under-resourced or rural settings. Moreover, whereas Tyrrell et al. used CNN and ResNet models to interpret ultrasound, the work reported herein achieved an 81.82% accuracy score by implementing a ViT + DenseNet121 model and presented the latter as a web app through Hugging Face Spaces so that it could be real time shared with patients easily.

4.3 Results and Discussion

The hybrid model (ViT + DenseNet121 with background) offered 81.82% validation accuracy, which is fit enough to apply in the real world. This model has been implemented through Hugging Face Spaces and developed as a lightweight, user-friendly web app available to the patient or healthcare provider. The users are able to upload joint bleeding pictures and quickly get the classification labels which can be used to tell the priority and severity of the joint bleeding. This instrument can be used to help detect early and intervene at the right time and is applicable in remote or areas where resources are scarce. I have selected the model to create .h5 file with best accuracy model which is the ViT + DenseNet121 with background. Then I have create a flask website and deploy to hugging face for all patient use. Make sure that this detection system is only workable to hemophilia affected joint bleeding cases. Because normal people joint condition is totally different to hemophilic patient joint as well.

Model based confusion Matrix:

<u>Xception (Basic CNN) with background</u>

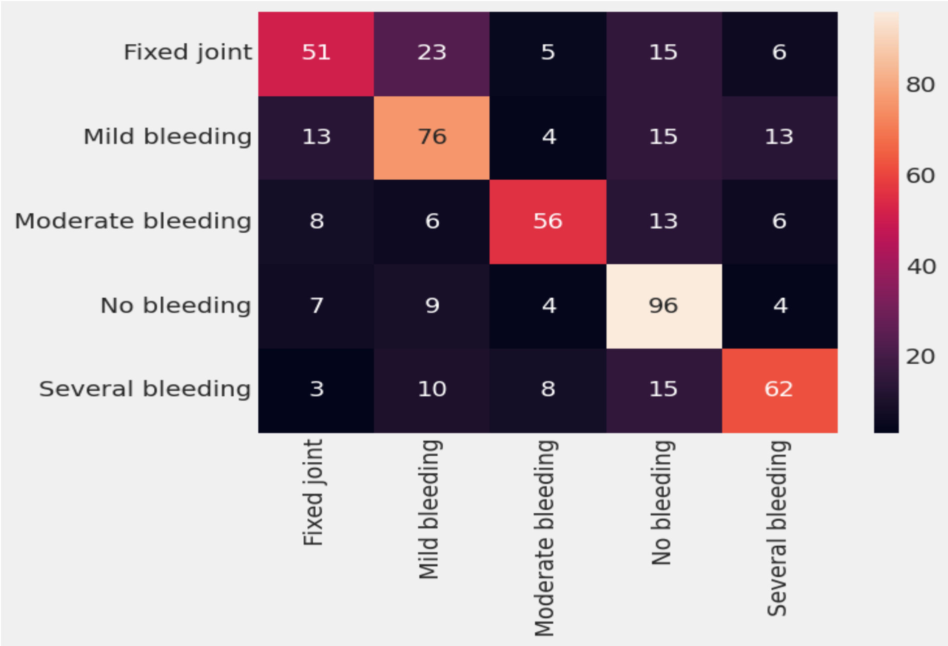

Figure 4.3.1: Confusion matrix (Xception)

The confusion matrix (Figure:4.3.1) of the joint bleeding detection model, trained on the Xception model without background removal, shows that it is working well predicting No bleeding (96 correct) and Moderate bleeding (56 correct), but it performs bad on Fixed joint (51/107) and Several bleeding (62/98) which can probably be attributed to the background noise. All in all, it is fairly accurate with potentials of refinement in the classification of severity of bleeding.

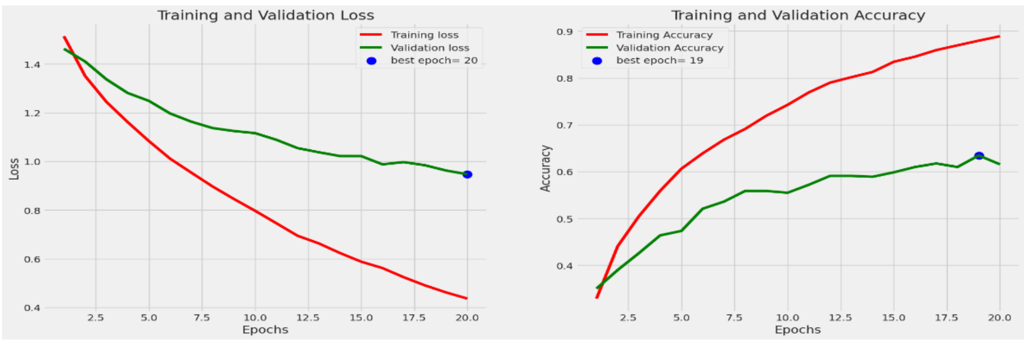

Figure 4.3.2: Training and validation Loss Accuracy(Xception)

The training and the validation curve measures the development of the model through 20 epochs. The loss (left) decreases to 0.8 to 1.4 during training and loss during validation remains quite high at around 1.0 by 20 epochs, pointing at the overfitting. By the best epoch, which is epoch 19, the accuracy (right) achieving 0.9 in training and 0.6 in validation. The gap indicates that model might be over-memorizing the training data, so halting at epoch 19 may help in performance on new data.

ViT + DenseNet121 with background

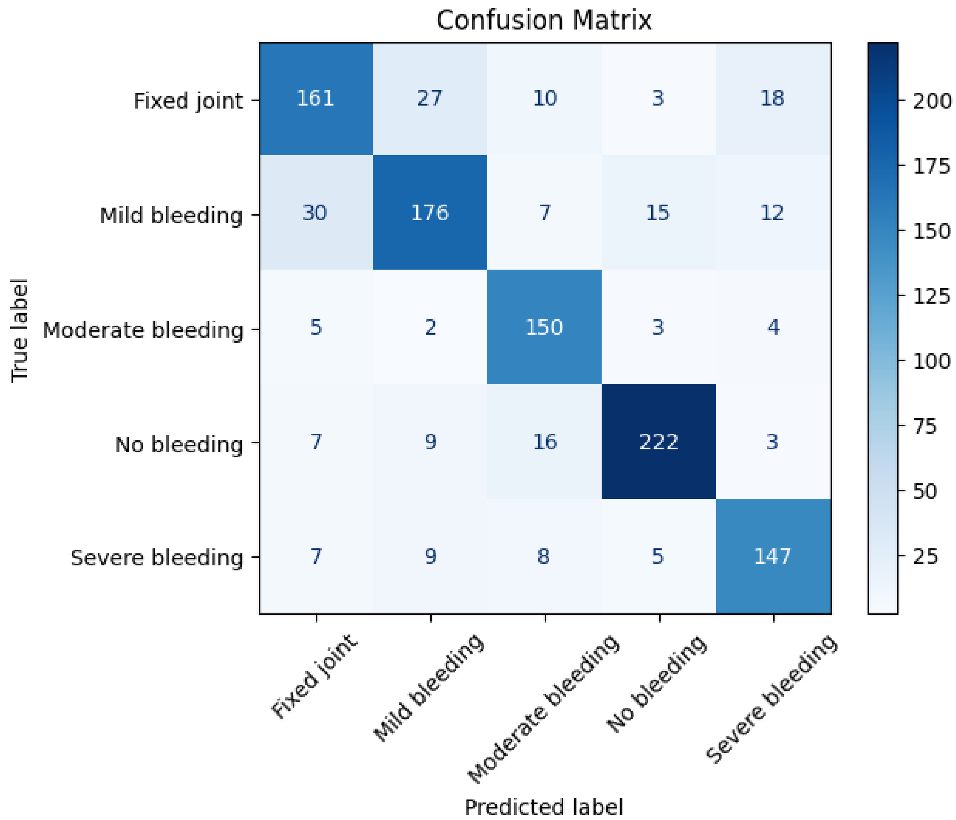

Figure 4.3.3: Confusion matrix (ViT + DenseNet121 with background)

The confusion matrix (Figure 4.3.3) of the joint bleeding detection model, ViT + DenseNet121 with background, demonstrates high performance in five categories and is fixed joint, mild bleeding, moderate bleeding, no bleeding, and a few bleeding. The model does very well in No bleeding (222 correct) and Mild bleeding (176 correct) but mediocre in Fixed joint (161 correct) and Several bleeding (147 correct). Nevertheless, it suffers in Moderate bleeding (150 correct of 169), which means some misclassification. All in all, the model works effectively, mostly in non-bleeding and mild cases, but can work in better discriminating moderate bleeding. This model is count a best model for this analysis as well.

In below figure:4.3.4, according to the training and validation graphs of the joint bleeding detection model the training accuracy is approximately 95 and validation accuracy settles on approximately 80 after 10 epoch which indicates good learning. Training loss stabilizes at around 0 and validation loss plateaus at about 0.6 which means that performance is high on training and a little overfitting occurs. All in all, the model possesses great potential and has the potential of enhancement in generalization through further tuning.

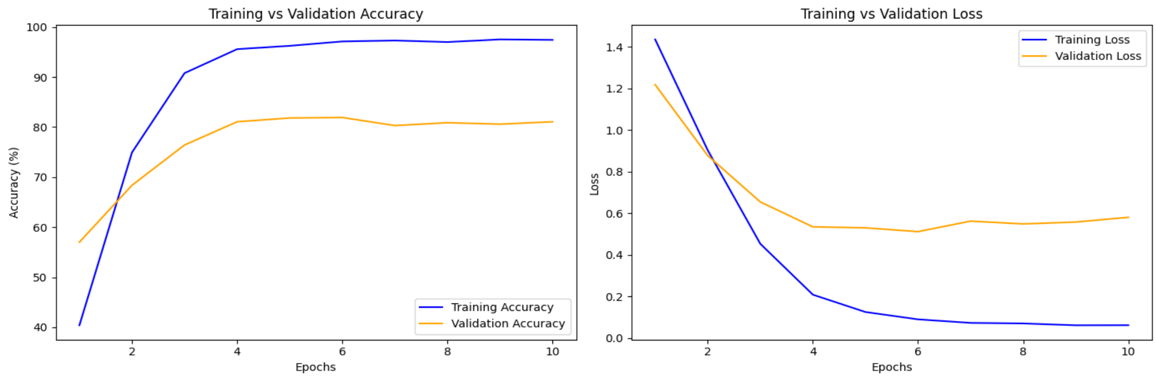

Figure 4.3.4: Training and validation Loss Accuracy (ViT + DenseNet121 with background)

<u>DenseNet121 removed background</u>

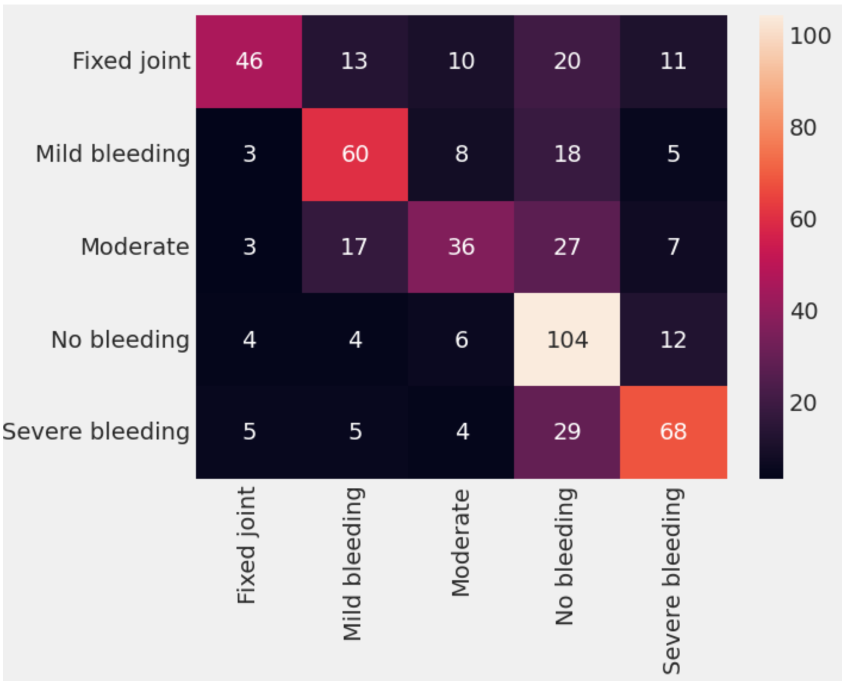

Figure 4.3.5: Confusion matrix (DenseNet 121 removed background)

The confusion matrix (Figure:4.3.5) of the joint bleeding detection model based on DenseNet121 without the layer of background is an indication of how superior it operates on the five different groups, namely Fixed joint, Mild bleeding, Moderate bleeding, No bleeding, and Severe bleeding. It shines when bleeding (No; 104 correct) and Mild bleeding (60 correct) and unsatisfactory when severe bleeding (68 correct). However, it does not handle Fixed joint (46 V content of 100 correct) and Moderate bleeding (36 V content of 83 correct), that is, it occasionally errs with these. All in all, it performs well at identifying no bleeding and mild cases but can be improved on the rest.

Figure 4.3.6: Training and validation Loss Accuracy (ViT + DenseNet121 with background)

According to the Figure 4.3.6, the training loss of joint bleeding detection model decreases to 1.0 at the 20th epoch where validation loss maintains a mean of 1.0, which indicates good model learning with minor overfitting. Accuracy of training is up to 0.7, and accuracy of validation is up to 0.6 at best epoch (epoch 18). The model is doing good with the capacity to do better with tuning on new data.

<u>ViT + DenseNet121 removed background</u>

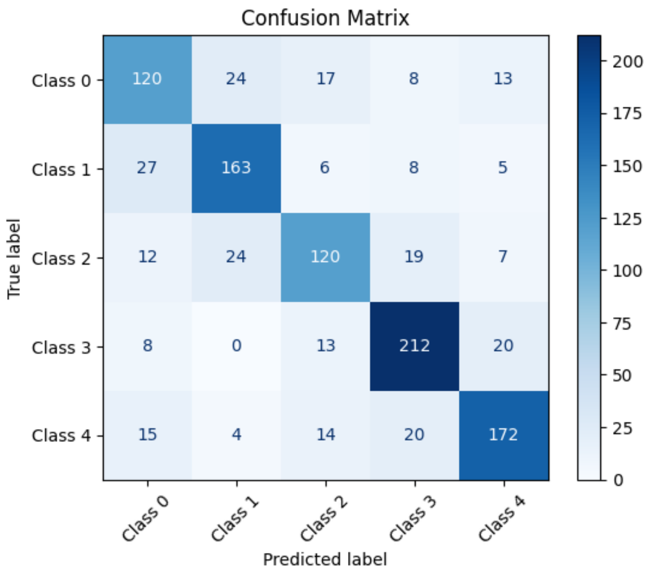

Figure 4.3.7: Confusion matrix (ViT + DenseNet121 without background)

According to confusion matrix (Figure 4.3.7) of the joint bleeding detection model with ViT + DenseNet121 without background noise, the model performs well by four classes. It performs well in Class 3 (212 correct) and Class 4 (172 correct) and, not badly in Class 0 (120 correct) and Class 1 (163 correct). But it suffers Class 2 (120 / 162 correct) and it has some misclassifications in other classes. All in all, the model is robust across the majority of categories but may be improved in classification concerning Class 2 and minimized error rates in other predictions.

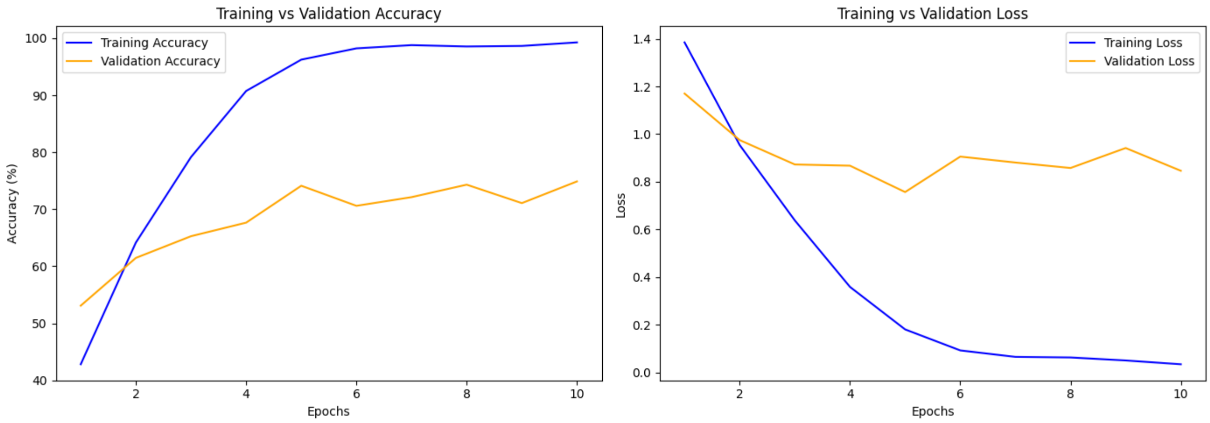

Figure 4.3.8: Training and validation Loss Accuracy(ViT + DenseNet121 without background)

According to the plots of the joint bleeding detection model, trained on ViT+DenseNet121 without background, the training accuracy increases to almost 95% and validation accuracy settles around 80 after 10 epochs which indicates well-learning. Training loss approaches 0, at the same time, the validation loss is stabilized around 0.6, which means that the training occurred successfully with limited overfitting. On the whole, the model is quite good and may be enhanced by some tuning to provide the generalization.

4.4 Summary

In this chapter we described the technical realization and evaluation of our deep learning-based hemophilia joint bleeding classification system. In the GPU enabled environment on Kaggle we've trained and tested 5,000 augmented images across a variety of models. Comparative examination witnessed the best performance using hybrid model using Vision Transformer (ViT) to excavate feature and DenseNet121 to perform classification because it demonstrated the highest validation accuracy (81.82%) when trained on original images containing background. When trained with images in which the background was filtered out, models slightly underperformed, which is indicative that visual context is critically important to proper classification. The chosen model is put to application through Hugging Face Spaces creating a convenient and web-based application on which real-time severity prediction can be done. The system will largely be beneficial in making prompt clinical decisions in terms of hemophilia patients, particularly those in remote or underserved areas.

Chapter 5

Engineering Standards and Design Challenges

This chapter shows the engineering standards of the development of the hemophilia joint bleeding detection system, social, and ethical and sustainability. It emphasizes adherence to software, hardware, and communication standards, and describes how such a system will affect patients, treating professionals, and society in general.

5.1 Compliance with the Standards

The project was to be implemented to coincide with the commonly accepted norms in the development of software, the use of hardware, and communication. The standards make the system dependable, scalable, and friendly to the users.

5.1.1 Software Standards

Python programming language and frameworks such as TensorFlow and PyTorch were used in implementing the system and are open-source and common in machine learning research. The practices used were similar to the industry including modularly coding programs, good documentation, and version control (Kaggle), which made the project easily maintainable. Deployments on Hugging Face Spaces followed best practices in modern software deployment in that it allowed deployment on an interface accessible via a browser; this is a secure manner. Advantages: Open source, reproducible, scalable, well supported.

1. Pros: Open source, reproducible, scalable, well supported.
2. Cons: Third party platform for deployment, compatibility problems.
3. Rationale of selection: Accessible, supported by the community, and affordable.

5.1.2 Hardware Standards

GPU resources were accessed on Kaggle to perform the model training whilst that high-performance computing standards were compatible without any physical investment of the hardware. To transfer and attach the images, patients will only require a typical smartphone or a computer to use the system to check the current joint bleeding situation and clinical report as well.

1. Pros: Free access to GPUs, hardware maintenance costs decrease, it can be used even in one-research studies.
2. Cons: Short period of training, the dependence on the Internet connection.
3. Rationale of selection: It selected as the least expensive, and accessible to students.

5.1.3 Communication Standards

The web-based application system implemented uses the familiar use of HTTP/HTTPS protocols to ensure the secure passage of data between users and the web application Hugging Face. Although it does not involve storage of any confidential information about patients, adherence to the data privacy principles (equivalent of HIPAA/GDPR) was taken into consideration in order to guarantee ethical treatment of medical information.

1. Pros: Encryption of security, universal, supported.
2. Cons: The reliance on the Internet can slow down access in local communities.
3. Rationale of selection: HTTPS is ubiquitous protocol that applies to safe communication, which makes it safe to use in healthcare setting.

5.2 Impact on Society, Environment and Sustainability

5.2.1 Impact on Life

It can be directly used to enhance the living conditions of hemophilia asthmatics by real time detecting of bleeding joint situation as well. Patients are able to make a realistic choice pertaining to possible home treatment to control the bleeding process or go to hospital to receive quality medical care thus cutting down on complications and wastage of time. Easily get the IU of factor injection will be needed for cure current bleeding condition as well. Delays for analysis could arise due to long travel which has the risk of increasing of bleeding. The system decrease the health risks by reducing the necessity to travel, therefore, limiting these health risks.

5.2.2 Impact on Society & Environment

The system saves the financial expenditures of patients and limits the carbon footprint caused by transportation by eliminating the necessity of regular travels to those specialized hospitals (e.g., Dhaka). A long trip may also have negative effects, because any delays tend to aggravate the situation and lead to severe attacks. Patients in rural settings are usually poor and in many cases illiterate and in that case it becomes difficult to adhere to advice issued by doctors. Towards this end, the training will be offered prior to the publication of the system to ensure that patients and their families are taught on the use and also can acquire reasonable recommendations on the early detection and early treatment.

5.2.3 Ethical Aspects

The system is based on using medical images so high ethical grounds are necessary to provide security and rationality. Such questions as the privacy of the data, patients consent, and the accuracy of AI predictions are of utmost importance. All the images that are collected were done so with the permission of the Hemophilia Society of Bangladesh in order to preserve confidentiality and no identifiable data about a patient was stored.

Key Ethical Measures:

1. Data privacy maintained by avoiding storage of personal identifiers
2. Patient consent ensured through proper authorization for collect image data
3. Images collected under the approval of the Hemophilia Society of Bangladesh
4. Fairness and reliability of AI predictions considered throughout development

5.2.4 Sustainability Plan

This project is sustainable because it is created on the basis of the frameworks that are open-source and free to utilize. It is also possible to supply the system with new images and retrained models on an ongoing basis to increase accuracy. Sustainability in the future can include partnership with health care facilities in expanding the dataset, validating in the clinical community, and deploying in the long term. Plan to introduce this system to the World Federation of Hemophilia so that everyone can use to detect the real time joint bl

5.3 Project Management and Financial Analysis

In this section, the cost analysis/financial planning of the project is presented. It also has estimated project budget which is needed to implement the project and a proposed way to get revenue. In order to achieve flexibility, an alternative budget is provided as well and a logic behind every decision. This assists in recognizing the economic viability and it also assists in planning various situations.

Table: 5.3: Budget analysis table

SN	Components	Cost (BDT)
01	Tools and Equipment (mobile, storage, etc.)	4500 – 6000
02	Visiting data collection sources (regional travel)	2000 – 3000
03	Software (Roboflow Pro, if upgraded, and Python libraries/tools)	1500 – 2000
04	Documentation and Report Writing	500 – 1000
05	Contingency (10% of total)	1000 – 1500
	Total Cost (BDT)	**9500 – 13,500**

5.4 Complex Engineering Problem

5.4.1 Complex Problem Solving

This table (Table 5.1) reflects mapping of this project with complex engineering problem criteria including level of knowledge, analysis, stakeholders involved and other factors that have been considered in the development of this project.

Table 5.1: Mapping with Complex Engineering Problem.

EP1 Dept of Knowledge	EP2 Range Of Conflicting Requirements	EP3 Depth of Analysis	EP4 Familiarity of Issues	EP5 Extent of Applicable Codes	EP6 Extent Of Stake-holder Involvement	EP7 Interdependence
✔	✔	✔	✔	✔	✔	

EP1: -This project needed expertise in the topic of hemophilia, medical imaging, and deep learning models. ViT and DenseNet121 concepts required sophisticated ideas in machine

learning and could not be learnt through mere programming. Need to know about some mathematical knowledge to calculate some area and factor dosages based on their age and weight.

EP2: During training these four model for both with background and without background of joint bleeding image data, a controversy matter happen where I have got more accuracy with background noise image data rather than after remove the background noise. Without background I have got very low accuracy.

EP3: Data preprocessing, additions, comparing different models (Xception, denseNet121, ViT), required a sophisticated experiment and analysis.

EP4: From my personal experiences of working with Hemophilia society of Bangladesh as a general secretary of National Youth committee I have seen many cases with joint bleeding hemophilia patient and also see how this patient come to our main office with this pain only get know the condition and doctor suggestion. It is very painful for them who travel a long road to come our main office with this joint bleeding pain.

EP5: This project was developed with popular AI/ML packages such as TensorFlow, PyTorch and Hugging Face. However, not many special rules and codes of hemophilia images classification are present. Adding new features to the system is also possible, and it would assist in increasing the accuracy.

EP6: A key stakeholder, the Hemophilia Society of Bangladesh, played an active role in the data collection but did so through the RYC (Regional Youth Committee) to make the research genuinely representative of practice and patient-centered design.

Mapping with Knowledge Profile

This table (table:5.2) is designed to map the overall problem and EP1 to the Knowledge Profile.

Table 5.2: Mapping with knowledge Profile.

K1 Natural Science	K2 Mathematics	K3 Engineering Fundamentals	K4 Specialist Knowledge	K5 Engineering Design	K6 Engineering Practice	K7 Comprehension	K8 Research Literature
	✔	✔	✔	✔	✔	✔	✔

K2 : Applied to several steps such as data augment, probability-based classification and measures. The effectiveness of the models had been trained using concepts such as accuracy, accuracy as calculated using validation, and error rate. Also, mathematics contributes significantly to the hemophilia treatment as the dosage needed to inject a factor (IU) is determined by the age, body weight, and intensity of bleeding of the particular patient thus establishing the connection between the clinical sphere and computational modeling.

K3 : Resting on the fundamentals of computer science and machine learning, including convolution neural networks(CNN), data preprocessing and model evaluation. These principles guaranteed the process of the work on the project adhered to the accepted principles of engineering in designing the AI systems.

K4: Necessary in the application of advanced architectures such as Vision Transformer (ViT) and DenseNet121. Expertise in transfer learning, feature embedding and fine-tuning deep models played an important role to obtain improved classification outcomes using the small amount of data. Also need to clear understanding of Hemophilia diseases as well.

K5: The design of the project came in stages: first we scraped and augmented images, then tried several different deep learning models, and finally settling on one with best performance (ViT + DenseNet121). Design decisions like not including background knowledge and developing the model for Hugging Face Spaces supported to prevent overfitting as well as accessibility, so that patients can readily assess their joint bleeding in real life situation.

K6: In this project, the Engineering Practice was undertaken to implement a medical issue with the use of computer vision and deep learning tools. The frameworks such as TensorFlow and PyTorch were used to develop the model, and Kaggle GPUs were utilized to assist in the training process. Hugging Face Spaces eventually deployed the system so that it could be accessed via the web. This demonstrates the way in which modern technology can be applied to healthcare in practice.

K7: This project uses AI to enhance healthcare through engineering in a safe and ethical manner, to help patients with hemophilia. It saves money, helps rural patients, reduces unnecessary travel, and makes it sustainable with open-source tools and web deployment

K8 : Heavily depended on to guide it in comprehending how hemophilia is dealt with, consult in the consideration of AI uses in medical diagnostics, and pertinent sets of data. The decision of using normal RGB images rather than ultrasound could be justified because of a literature review that made the system more affordable within Bangladesh. Most of the literature I have found to analysis medical history of hemophilia. Application of AI technology is very rare as well.

5.4.2 Engineering Activities

In this part of the paper, project is mapped to various engineering activities (EAs). Every EA is a significant component of the engineering work, including the use of the resources, communication with the other people, the introduction of innovations, understanding of the societal and environmental impacts, and surrounding familiarity with the work. The table(table:5.3) below demonstrates what activities are touched on in the project.

Mapping with Complex Engineering Activities

This section is designed to map the overall problem and EA's.

Table 5.3: Mapping with Complex Engineering Activities.

EA1 Range of resources	EA2 Level of Interaction	EA3 Innovation	EA4 Consequences for society and environment	EA5 Familiarity
✔	✔	✔	✔	✔

EA1: For making this project we need to collect 2000 real joint bleeding images from hemophilia patient in different part of Bangladesh by the help of RYC under Hemophilia Society of Bangladesh. These images are authentic by the society office and collected with a full concern of each patient as well.

EA2: We need to seat with the Executive member committee of Hemophilia Society of Bangladesh for show up the overall plan of this research and developing the system as well. We also take interview of several hemophilia patient to gathering main requirement and the daily base problem regrading hemophilia joint bleeding they are facing.

EA3: I have seen many literature study and system regarding hemophilia but there is no directly image based joint bleeding situation analysis tool as well. One system I have found in a study that only use Ultrasound images but that is very costly as well. So, this innovation will be play a vital role to analysis joint bleeding detecting in the hemophilia world.

EA4: As we know that each hemophilia patient belongs with a very painful story of their life. Every phase of their life they face many problems to analysis their bleeding and get a correct treatment as well. In Bangladesh many patients come to Dhaka for analysis and treatment for bleeding situation. So, with this project patient can easily get solution in home and no need to come to Dhaka for solution as well.

5.5 Summary

Chapter 5 points out that Hemophilia Joint Bleeding Detection System was prepared with the software, hardware and communication standards that made it reliable, accessible and ethically acceptable. The advantages of the system to the patients consist of it providing real-time home detection, and eliminating the travel time, costs and health risks, societal, environmental and ethical considerations as well. The financial planning demonstrates a viable cost (BDT 9,500-13500) that has options of flexibility. The project is dealing with multifaceted engineering problems, integrating the fields of AI, medical imaging, and hemophilia knowledge, and represents an innovative tool useful to stakeholders, sustainable in its applicability over a long period of usage.

Chapter 6
Conclusion

This chapter has overviewed the main results of the project, explained its drawbacks at the stage of project development, and made suggestions about possible future actions. This aim was to come up with AI-based clinical decision support system classification of joint bleeding severity in hemophilia patients which is based on deep learning approaches.

6.1 Summary

The goal of the project is help to diagnose and treat the hemophilia-related joint bleeding through image classification deep learning system development. 2000 authentic patient images were gathered with the help of the Regional Youth Committee (RYC) of the Hemophilia Society of Bangladesh. Augmentation techniques were used to increase the total number of images to 5,000 to provide better model performance and robustness with Roboflow. A range of models has been trained on a GPU environment with various architectures and preprocessing approaches being compared using Kaggle. The ViT with DenseNet121 was the best with a validation accuracy rate of 81.82%, especially at no background removal of the image. This model was trained and used in the context of Hugging Face Spaces to provide an accessible and real-time web application to be used in clinical practice as a clinical tool by healthcare providers and patients. The system is a valuable facilitation toward promoting quicker and precise diagnosis in low-income regions or even in rural regions.

6.2 Limitation

1. The dataset is relatively small and may not represent the global diversity of hemophilia patients and conditions, even after augmentation.
2. Images vary in lighting, quality, and angle, introducing noise that can reduce classification accuracy.
3. The web application is cloud-hosted, requiring a stable internet connection and some technical knowledge, which may be challenging in low-resource or rural

areas.

4. Many patients are live in rural area and most of them are illiterate, so it might be hard to use without pre-training season to how to use this system.

6.3 Future Work

A variety of streams to make it more accurate, convenient and effective in a real healthcare setting are possible. First, to increase the size of the dataset, through the association with more hospitals and international organizations, they want to include more bleeding cases and demographic variations. Later versions, will be able to accept clinical metadata, as well as images, to make a more comprehensive and precise diagnostic tool. Developing an app based on a mobile application would benefit usage to a large extent and would help in remote or under-resources areas. Explainable AI (approaches must also be incorporated so that the healthcare professionals can know how the model works to come on the prediction and this creates more trust and transparency. Finally, the model might have been improved upon with a process of constant learning or fine-tuning, one that is capable of changing over time as more data regarding patients is provided.

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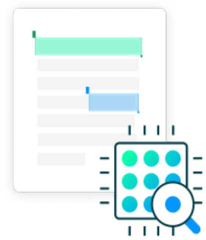

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AI detection scores under 20%, which we do not surface in new reports, have a higher likelihood of false positives. To reduce the likelihood of misinterpretation, no score or highlights are attributed and are indicated with an asterisk in the report (*%).

The AI writing percentage should not be the sole basis to determine whether misconduct has occurred. The reviewer/instructor should use the percentage as a means to start a formative conversation with their student and/or use it to examine the submitted assignment in accordance with their school's policies.

What does 'qualifying text' mean?
Our model only processes qualifying text in the form of long-form writing. Long-form writing means individual sentences contained in paragraphs that make up a longer piece of written work, such as an essay, a dissertation, or an article, etc. Qualifying text that has been determined to be likely AI-generated will be highlighted in cyan in the submission, and likely AI-generated and then likely AI-paraphrased will be highlighted purple.

Non-qualifying text, such as bullet points, annotated bibliographies, etc., will not be processed and can create disparity between the submission highlights and the percentage shown.