

STOMACH PROBLEMS DETECTION USING MACHINE LEARNING

Submitted in partial fulfillment of the requirements for the award of
Bachelor of Engineering Degree in Electronics and Communication Engineering

by

K. SAI SHARANYA (40130096)

S.HARIPRIYA (40130077)



**DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING
SCHOOL OF ELECTRICAL AND ELECTRONICS**

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JEPPIAAR NAGAR, RAJIV GANDHI SALAI, CHENNAI – 600119

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BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **HARIPRIYA.S (40130077)** and **SAI SHARANYA.K (40130096)** who carried out the project entitled "**STOMACH PROBLEMS DETECTION USING MACHINE LEARNING**" under our supervision from November ,2023 to April 2024.

Internal Guide

Dr.G. JEGAN, M.E., Ph.D.

Head of the Department

Dr. T. RAVI, M.E., Ph.D.

Submitted for Viva voce Examination held on 17.04.2024

Internal Examiner

External Examiner

DECLARATION

We HARIPRIYA.S (40130077) and SAI SHARANYA.K (40130096) here by declare that the Project Report entitled "STOMACH PROBLEMS DETECTION USING MACHINE LEARNING " done by us under the guidance of Dr.G.JEGAN M.E, PhD., Dept. of Electronics and Communication Engineering, SATHYABAMA INSTITUTE OF SCIENCE AND TECHNOLOGY, CHENNAI, is submitted in partial fulfillment of the requirements for the award of Bachelor of Engineering degree in Electronics and Communication Engineering.

DATE: 17.04.2024

PLACE: Chennai

SIGNATURE OF CANDIDATES

1. HARIPRIYA.S - *Haripriya.S*

2.

BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **SAI SHARANYA.K (40130096) and HARIPRIYA.S (40130077)** who carried out the project entitled **“STOMACH PROBLEMS DETECTION USING MACHINE LEARNING”** under our supervision from November2023 to April 2024.

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DATE:

PLACE: Chennai

SIGNATURE OF CANDIDATES

1.

2.

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ABSTRACT

Gastrointestinal (GI) bleeding is very common in humans, which may lead to fatal consequences. GI bleeding can usually be identified using a flexible wired endoscope. In 2001, a newer diagnostic tool, wireless capsule endoscopy (WCE) was introduced. It is a swallow-able capsule-shaped device with a camera that captures thousands of color images and wirelessly sends those back to a data recorder. But it takes a longer screening time which may increase the danger of the patients in emergency cases. It is therefore necessary to use a real-time detection tool to identify bleeding in the GI tract. Medicine is one of the rich sources of data, generating and storing massive data, begin from description of clinical symptoms and end by different types of biochemical data and images from devices. Manual search and detecting biomedical patterns is complicated task from massive data. Data mining can improve the process of detecting patterns. Stomach disorders are the most common disorders that affect over 60% of the human population. In this work, the classification performance of four non-linear supervised learning algorithms i.e. Logic, K-Nearest Neighbor for two types of stomach disorders are compared and discussed. The objectives of this research are to find trends of using or improvements of machine learning algorithms for detecting symptoms of stomach disorders, to research problems of using machine learning algorithms for detecting stomach disorders. Bayesian optimization is considered to find optimal hyper parameters in the algorithms, which is faster than the grid search method.

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LIST OF ABBREVIATIONS

ATL	Amount of transmitted light
AUC	Area under the curve
BIC	Bayesian information criterion
BS	Blood samples
CADSS	Computer-aided decision support scheme
CCD	Charge coupled device
CE	Capsule endoscopy
CMOS	Complementary metal-oxide semiconductor
CNN	Convolutional neural network
CP	Cut-off point
CWE	Conventional wired endoscopy
EDTA	Ethylene-diamine tetra-acetic acid
EM	Expectation-maximization
FWHM	Full-width half-max
GI	Gastrointestinal
Hb	Hemoglobin
LED	Light emitting diode
LGA	Land grid array
LPB	Local binary pattern
MAE	Mean absolute error
ML	Maximum likelihood
MLA	Machine learning algorithm
MSE	Mean squared error
NBS	Non-blood samples

CHAPTER 1

INTRODUCTION

Gastrointestinal dying (GI drain), moreover called gastrointestinal hemorrhage (GIB), is all shapes of dying in the gastrointestinal tract, from the mouth to the rectum. When there is critical blood misfortune over a brief time, side effects may incorporate heaving ruddy blood, spewing dark blood, wicked stool, or dark stool. Little sums of dying over a long time may cause iron-deficiency frailty coming about in feeling tired or heart-related chest pain. Other indications may incorporate stomach torment, shortness of breath, pale skin, or passing out. In some cases, in those with little sums of dying no indications may be present.

Bleeding is ordinarily isolated into two primary sorts: upper gastrointestinal dying and lower gastrointestinal bleeding. Causes of upper GI drains incorporate: peptic ulcer malady, esophageal varices due to liver cirrhosis and cancer, among others. Causes of lower GI drains incorporate: hemorrhoids, cancer, and fiery bowel infection among others. Little sums of dying may be recognized by fecal mysterious blood test. Endoscopy of the lower and upper gastrointestinal tract may find the range of bleeding. Restorative imaging may be valuable in cases that are not clear.

Machine Learning is a type of intelligence that comes from machines or computer systems that mimics human cognitive function. Recently, ML has been utilized in medicine and helped clinicians make clinical decisions. In gastroenterology, AI has assisted colon polyp detection, optical biopsy, and diagnosis of *Helicobacter pylori* infection. ML also has a broad role in the clinical prediction and management of gastrointestinal bleeding.

Machine learning can determine the clinical risk of upper and lower gastrointestinal bleeding. ML can assist the management of gastrointestinal bleeding by identifying high-risk patients who might need urgent endoscopic treatment or blood transfusion, determining bleeding stigmata during endoscopy, and predicting recurrence of gastrointestinal bleeding.

The present review will discuss the role of ML in the clinical prediction and management of gastrointestinal bleeding, primarily on how it could assist gastroenterologists in their clinical decision-making compared to conventional methods.

Several scoring systems or risk models have been developed to predict the clinical risk of GI bleeding. In patients using antithrombotic medications, these risk models include HAS-BLED (hypertension, abnormal kidney and liver function, stroke, bleeding, labile international normalized ratio, elder age, and drug or alcohol use), ATRIA (anticoagulation and risk factors in atrial fibrillation), ORBIT (Outcomes Registry for Better Informed Treatment of Atrial Fibrillation), and HEMORR2HAGES (hepatic or kidney disease, ethanol abuse, malignancy, older age, reduced platelet count or function, rebleeding, hypertension, anemia, genetic factors, excessive fall risk, and stroke). Among these models, HAS-BLED has the best performance to predict major bleeding events.

Compared to the previous risk models, the prediction model using machine learning is hypothesized to have better performance since it can utilize more extensive and updated data sets. Three machine learning algorithms: Regularized Cox regression (RegCox), random survival forests, and extreme gradient boosting (XGBoost) on adult patients who were prescribed antithrombotic drugs (vitamin K antagonists, direct oral anticoagulants (DOACs), and/or thienopyridine antiplatelet agents) to predict the probability of GI bleeding at 6 and 12 mo. The data were obtained from medical and pharmacy claims data of 300000 patients. They also compared the performance of the machine learning algorithms to the HAS-BLED risk model.

Machine learning algorithms that utilize real-time data, such as RegCox, should better predict GI bleeding than the scoring systems mentioned above. Moreover, machine learning algorithms can provide time-to-event outcomes that can be used in the prediction of both short-term and long-term GI bleeding events. used data sets from insurance claims and could not provide actual clinical values, which might contribute to low AUCs in their study.

Data sets from electronic health record data that contain laboratory values and endoscopic reports might result in a better accuracy for clinical prediction of GI bleeding.

1.1 INTRODUCTION TO WIRELESS CAPSULE ENDOSCOPY

Wireless capsule endoscopy (WCE) is a procedure that captures images of the digestive tract using a tiny wireless camera. It is a non-invasive, painless endoscopic technique that can be used for diagnostic and other medical experiments to screen all components of gastrointestinal tract. In medical terms, capsule endoscopy is a method for observing the esophagus, stomach, small intestine, and colon within the GI tract. WCE does not require any needles, fluids or instruments to be inserted into the body due to its non-invasive nature.

In a vitamin-sized capsule, the patient swallows a capsule endoscopy (CE) camera. As the capsule travels through the digestive tract, the camera takes thousands of images that are transmitted to a data recorder worn around the waist using a belt. On the other hand, traditional endoscopy includes passing down the throat or through the rectum through a lengthy, flexible tube fitted with a video camera. There are different types of endoscopy procedures such as cystoscopy, colonoscopy, anoscopy, gastroscopy, etc

The procedures are classified on the basis of their region of operation and endoscopy application. Prior to the development of the WCE, the small intestine could only be explored by invasive procedures (intraoperative enteroscopy) or poorly effective methods, such as small bowel series. Traditional endoscopy can create discomfort and have some risks. Over sedation, cramps, persistent pain, or even tissue perforation and minor internal bleeding are some of the major side effects of traditional endoscopies.

In addition, it is also restricted to travel within the entire GI tract's abdomen and duodenum. On the contrary, WCE a small electronic device and an advanced version of traditional endoscopy which has overcome these limitations. Extensive

accessibility of WCE, which permits better visualization of the mucosa with few complications, has led to a revolution in small intestinal endoscopy and a substantial boost in CE signs. It helps doctors see within the small intestine - an area that is not easily reached through traditional endoscopy procedures.

In patients suspected of bleeding and other kinds of abnormalities such as Crohn's disease in GI, WCE imaging is a must. It can be used for patients with the syndrome of polyposis and small bowel disorder. It also identifies celiac disease, inflammation, swelling, ulcers, bleeding, tumors, lesions, pre-cancer abnormalities, and blockages [6]. It can be endorsed to assess the muscle tube connecting the patient's mouth and belly (esophagus) to search for unusual, enlarged veins (varices).

There are several contraindications to capsule endoscopy. Since the procedure requires patient participation, individuals with dementia are usually poor candidates. Swallowing disorders may cause difficulty in ingesting the capsule. There is a relative contraindication in patients with cardiac pacemakers, defibrillators, or left ventricular assist devices due to a concern for possible interference between the capsule and the cardiac devices.

However, there has never been a reported case of cardiac device malfunction due to capsule endoscopy. Furthermore, studies have demonstrated that there is no interference with these cardiac devices. Many centers still perform the capsule endoscopy in patients with cardiac devices. Pregnant women should not have capsule endoscopy since there are no studies on the safety of capsule endoscopy in this patient population. The risk of capsule retention is greatest in patients with known or suspected strictures, fistulas, and obstructions.

Capsule endoscopy is contraindicated in these patients due to the risk of worsening obstructions or causing obstructions. If capsule endoscopy is necessary for a patient at risk for retention, an Agile Patency Capsule can be ingested. Agile Patency Capsule is a radiopaque capsule without video capabilities. Thirty hours after ingestion a plain abdominal film or hand-held scanner can be used to

determine the passage of the capsule. This determines if it is safe to proceed with video capsule endoscopy. If the Agile Patency Capsule is retained, it will dissolve and pass safely through the gastrointestinal tract.

The video capsule can also be retained due to achalasia, esophageal diverticula, esophageal strictures, or pyloric stenosis. Gastroparesis may slow the mobilization of the capsule. In these types of patients, an Advance Capsule Endoscopy Delivery System can be attached to the tip of a gastroscope which can then be used by the endoscopist to place the capsule in the stomach or duodenum. Capsules can also be placed into the stomach through the use of an over tube or advanced from the stomach into the duodenum with nets.

Preparation for a capsule endoscopy is similar to that of colonoscopy preparation and can be performed in an outpatient setting. The day before the procedure patients should remain on a clear liquid diet. Patients need to fast for 10 to 12 hours before video capsule ingestion. Polyethylene glycol solution can be taken the night before the study which helps clear food and stool debris out the gastrointestinal and may improve visualization.

For colon capsule endoscopy the patient is required to consume at least 3 liters of polyethylene glycol solution to evacuate the colon. There are mixed reviews whether prokinetic agents such as metoclopramide and erythromycin improve the passage of capsules through the gastroenterology tract. Simethicone solution has been used to improve visualization by decreasing air bubbles in the intestinal lumen.

1.2 INTRODUCTION TO GASTROINTESTINAL BLEEDING

Any form of bleeding that occurs in a tract of human GI is called gastrointestinal bleeding. In several cases, it may be a life-threatening issue, if not properly diagnosed and addressed in time. Based on abnormality symptoms, clinicians conduct various medical exams to verify the nature and source of bleeding. Endoscopy is one of the procedures for detecting GI bleeding. GI bleeding can mainly be classified as overt, occult or obscure bleeding.

1.2.1 EPIDEMIOLOGY OF OBSCURE GASTROINTESTINAL BLEEDING(OGIB)

Obscure gastrointestinal bleeding is defined as persistent or recurrent bleeding associated with negative results from endoscopic evaluations of the upper and lower gastrointestinal tract. Depending on the existence or lack of clinically obvious bleeding, OGIB may be further categorized into overt or occult bleeding. Overt OGIB is described as noticeable GI bleeding (e.g. melena or hematochezia) and may be classified as active or inactive bleeding since there is proof of continuing bleeding.

OGIB is categorized as occult when there is no proof of visible GI bleeding such as unexplained anemia with iron deficiency suspected of causing GI blood loss. A prevalent clinical presentation of gastrointestinal bleeding is about 1 case per 1,000 people per year. OGIB accounts for about 5% of all GI bleeding instances, with tiny intestines as the suspected cause. This has resulted in the new word "mid-gastrointestinal bleeding" being used to define bleeding between the papilla and the ileocecal valve. Diagnosis.

Management of OGIB patients are especially difficult due to the small intestine's long and complicated loops. The symptoms present may assist to guide the inquiry plan. Hematemesis may show upper GI swelling, while melena may suggest bleeding from the nose to the large bowel anywhere. In contrast, hematochezia (the presence of blood and blood clots in the feces) suggests either a reduced GI bleeding or a rapidly higher GI bleeding.

1.2.2. Causes of Obscure Gastrointestinal Bleeding

Obscure gastrointestinal bleeding may result from any lesion throughout the GI tract, although most of it occurs in the small intestine and mainly involves vascular lesions. The rate of OGIB is around 5% among all the patients with gastrointestinal bleeding [98]. Bleeding etiology in the small intestine is diverse and may depend on the patient's age. Tumors, meckel's diverticulum, dieulafoy's lesion, crohn's disease, celiac disease, etc. are the most common cause of OGIB in patients younger than 40 years.

On the other hand, in patients 40 years older, angiectasia, nonsteroidal anti-inflammatory drug, enteropathy, vascular ectasias, celiac diseases are the most common causes of OGIB. There are still some uncommon causes of OGIB which includes hemobilia, hemosuccus pancreaticus, aortoenteric fistula, long-distance running, etc. Many conditions can cause GI bleeding. A doctor can try to find the cause of your bleeding by finding its source. The following conditions, which are listed in alphabetical order, include possible causes of GI bleeding:

Angiodysplasia. Angiodysplasia is when you have abnormal or enlarged blood vessels in your GI tract. These blood vessels can become fragile and bleed.

Benign tumors and cancer. Benign tumors [NIH external link](#) and cancer [NIH external link](#) in the esophagus, stomach, colon, or rectum may cause bleeding when they weaken the lining of the GI tract. A benign tumor is an abnormal tissue growth that is not cancerous.

Colitis. Ulcers in the large intestine are a complication of colitis. Ulcerative colitis is an inflammatory bowel disease that can cause GI bleeding.

Colon polyps. Colon polyps can cause GI bleeding. You can have more than one colon polyp at a time. Some types of polyps may be cancerous or can become cancerous.

Diverticular disease. Diverticular disease can cause GI bleeding when small pouches, or sacs, form and push outward through weak spots in your colon wall.

Esophageal varices. Esophageal varices can cause GI bleeding. Esophageal varices are usually related to a chronic liver condition called cirrhosis.

Esophagitis. The most common cause of esophagitis is gastroesophageal reflux (GER). GER happens when your lower esophageal sphincter is weak or relaxes when it should not. Stomach acid can damage your esophagus and cause sores and bleeding.

Gastritis. Some common causes of gastritis include the use of nonsteroidal anti-inflammatory drugs (NSAIDs) and other medicines. Infections, Crohn's disease, serious illnesses, severe injuries. If untreated, gastritis can lead to ulcers or worn-away areas of the stomach lining that can bleed in your GI tract.

Hemorrhoids or anal fissures. Hemorrhoids can cause GI bleeding. Constipation and straining during bowel movements cause hemorrhoids to swell. Hemorrhoids cause itching, pain, and sometimes bleeding in your anus or lower rectum. Anal fissures are small tears that also can cause itching, tearing, or bleeding in your anus.

Mallory-Weiss tears. Severe vomiting may cause Mallory-Weiss tears, which can cause GI bleeding. You can have more than one Mallory-Weiss tear at a time.

Peptic Ulcers. The bacteria *Helicobacter pylori* (H. pylori) and use of NSAIDs can cause peptic ulcers. Peptic ulcers can wear away your mucosa and cause GI bleeding.

CHAPTER 2

LITERATURE REVIEW

2.1 LITERATURE SURVEY

In 1806, Phillip Bozzini, known as "Father of Endoscopy," demonstrated a light conductor (Lichtleiter) that allowed a direct view into the living body. Antonin Jean Desormeaux first used the term 'endoscopy' in 1853. In 1954, "Fiberscope" was created as an optical unit that transmitted optical images along a flexible axis. In 1955, a French bronchoscopy team broadcast on live television their endoscopic technique. Dr. V. K. Zworykin launched the first wireless machine to send GI tract data in 1957. It was called "Radio Pill" and consisted of a plastic capsule with a length of 1.125 inches and a diameter of 0.4 inches. Signals were transferred according to the pressure.

In 2001, a firm named Given Imaging launched a full capsule endoscopy with self-illumination, camera, battery, processor, and transmitter. A data recorder device obtains all the related information from the capsule. A typical block diagram of WCE system is shown in Fig. 2.1

A typical block diagram of a wireless capsule endoscopy capsule sends the captured images to the data recorder via suitable wireless communication. Then the outputs will be analyzed to diagnose the defects. Fig.2.2 released some updated versions of its products like PillCam SB 2, SB 3, ESO 2, ESO 3, Colon 2. Some other companies also introduced their products onto the market like Intromedic, Olympus, JinShan Science, and CapsoVison.

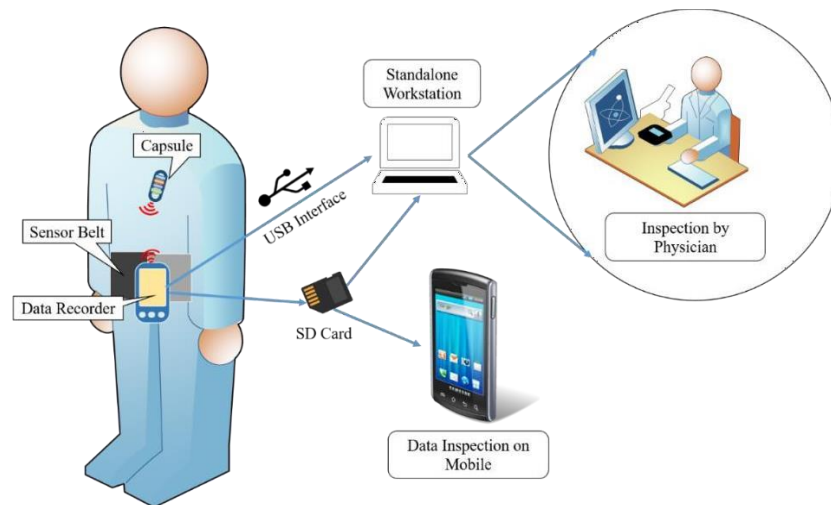


Figure 2.1: A complete system of wireless capsule endoscopy

Given Imaging's first capsule endoscope was PillCam SB, concentrating primarily on the small intestine. Given Imaging had also

Device	PillCam SB3	PillCam ESO2	PillCam Colon2	MiroCam	Endo Capsule	OMOM	CapsoCam
Company name	Given Imaging		Intromedic	Olympus		JinShan	CapsoVision
Region of operation	Small bowel	Esophagus	Colon	Small bowel	Small bowel	Small bowel	Small bowel
Dimension (mm)	11.4x26.2	11 x 26	11 x 31	10.8 x 24.5	11 x 26	13 x 27.9	11 x 31
Mass (gm)	3.0	2.9	2.9	3.25	3.3	≤6	4
Battery life	≥8 hr	0.5 hr	10 hr	12 hr	12 hr	6-8 hr or longer	~15 hr

Field of view	156°	172°	172°	170°	160°	140° ±10	360°
Frame rate (fps)	2 or ~6	35	4 or 35	3	2	0.5 or 2	3 or 5
Type of image sensor	1 CMOS	2 CMOS	2 CMOS	1 CMOS	1 CCD	1 CMOS	4 CMOS
Resolution	256x256	256x256	256x256	320x320	1920x1080	640x480	1920x1080
Transmission	RF	RF	RF	HBC	RF	RF	USB

Table 2.1: Comparisons of capsule endoscopy available in the market

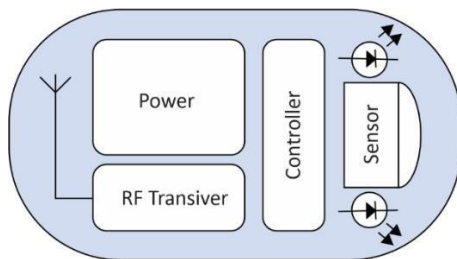
Table 2.1 shows a brief comparison of the existing capsule endoscopy products. Given Imaging was the first who came up with a solution of automated bleeding detection using their PillCam SB2 capsule. The capsule system had an embedded software called suspected blood indicator (SBI) which could mark the red areas in the frames as the potentially blood which eventually speeded up the bleeding detection diagnosis. Furthermore, to explore the esophagus PillCam ESO was launched, and PillCam Colon was launched to examine the colon. Jinshan Science and Technology had also developed the OMOM impedance-pH capsule wireless monitoring system which integrated both pH sensor and impedance sensor to monitor patient's pH and impedance data continuously within the esophagus for diagnosing GI function disorders. Most of these commercial capsule endoscopy systems only provide video or image capturing options. Also, there does not have any automated bleeding detection system in some of the systems to reduce the diagnosis time. On the other hand, the systems which have bleeding detection capabilities are usually based on the color properties of the blood which may provide wrong result as the blood color could vary from light red to dark red.

brown. So, it could be very difficult for these commercial endoscopy devices to separate blood from non-blood samples since these devices are not using any optical sensors to observe the optical characteristics of blood. Therefore, in this research, an optical sensor-based blood detection system has been proposed using machine learning techniques to solve such problems.

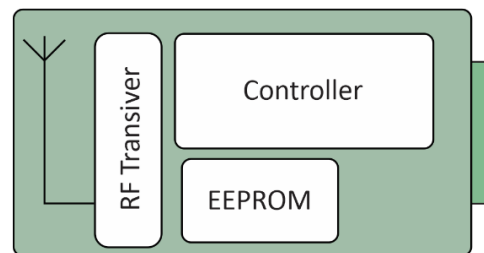
2.1.1. Structure of a Typical Capsule Endoscopy System

The WCE system has three different parts - a) a capsule with a camera, b) a datalogger for receiving the capsule's data wirelessly, and c) a computer software, to download and analyze recording information. Accurate inspection of a WCE readings is time-consuming and requires concentrated, undivided attention, as anomalies can occur within the range of a very few frame.

On average, it takes approximately 1-2 hours to visualize all the images. However, some WCE device manufacturers have made an effort to develop computer aided software that could reduce the time required to analyze the



(a) Capsule



(b) Datalogger



(c) Software

Figure 2.2 : Wireless capsule endoscopy components

capsule generally has a modular structure, which consists of four layers- i) imaging sensor layer, ii) processing unit layer, iii) RF transceiver layer, and iv) power management layer. The overall block diagram of the capsule is shown in Fig. 2.3 (a). The modular structure of the capsule does not require separate modules and makes it more versatile for practical usage. The whole system could be used or modified for different purposes depending on its application. The capsule's size and power consumption should be in a limited range. Therefore, components were chosen considering performance, power requirement and packaging size during the designing process.

The data logger is capable of receiving the capsule's signal and then transmitting the data to a computer. The data logger usually has two modes of operation. First, when a data logger is plugged into a computer via USB port, it enters into the "Software" mode operation. In this mode, the data logger receives signals from the capsule and transmits it to the computer in real-time. On the other hand, when the data logger is powered up by an external power source without having any connection to the computer, the device enters into the "Standalone" mode. In standalone mode, the data logger still receives data from the capsule but stores them into the built-in memory like EEPROM or SD card. By connecting the data logger to the computer, the WCE software could read the stored image or sensor data. The workstation software depends heavily on the WCE scheme.

When administered to a human body, a typical endoscopy capsule operates for about 8 to 10 hours and produces around 50,000 frames. A doctor still has to sit before the computer to determine any faded or unreliable frame. While there could be some features that could assist the doctor to automate abnormality detection, the current systems are still inefficient and unreliable in providing such features. The information recorded on the data logger will be obtained at a workstation during post-processing, where the software is configured to evaluate the information recorded. The respective manufacturer of the commercial WCE system provides the analyzing software. Different WCE manufacturers have developed software with multiple features which are frequently maintained and updated. For example, PillCam develops and provides RAPID reader software which includes some advanced functionalities that help physicians with automatic bleeding detection.

2.1.2. Clinical Need and Target Population

Since bleeding is a common symptom for many GI diseases, it has major clinical importance for the diagnosis of the relevant diseases. After endoscopy or colonoscopy does not disclose the origin of bleeding to explore the blood loss. Conventional methods, like gastroscopy and colonoscopy, face problems and cause a lot of pain when examining the small intestine.

On the contrary, because of WCE's non-invasive nature, it primarily is gaining popularity. It is safe, painless, free from infection and does not require sedation. It has a higher diagnostic efficiency than many other methods for assessing intestinal lumen and can find lesions. The main problem of WCE is the long period of medically- assessed bleeding detection steps in the entire GI tract. In addition, smaller bleeding regions and bleeding within a few frames sometimes may not be detected with naked eyes. Therefore, several researchers have given a lot of attentions to the automation of the bleeding detection system.

2.1.3. Thesis Objective

The goal of the thesis is to develop a machine learning classifier model that can be used to differentiate GI blood from other non-blood substances. To achieve the goal, the following research objectives are set:

- (a) To explore the spectrum of wavelengths for separating the blood and non-blood samples. These experiments could be carried out using two 6-channel spectral sensors- one in the visible spectral region (AS7262) and other in the infrared spectral region (AS7263).
- (b) To develop a machine learning classifier model for predicting the bleeding, from non-blood and blood samples by considering specified spectral wavelengths as the features for the model.

2.1.4. Thesis Organization

The thesis is structured in eight chapters. A short description of each of the chapters and sections are given below:

Chapter 1: Introduction presents the overview of the WCE system, clinical needs of wireless endoscopy system, the motivation of the thesis, thesis organization.

Chapter 2: The chapter discusses the related literature works on detecting bleeding in the GI tract in the WCE systems. It also provides the overview of the systems which are being used in the commercial capsule endoscopy systems as well.

Chapter 3: The chapter represents the research motivation of the thesis. It also discusses the sample collections procedures which are used for validating the proposed methods. In order to obtain the best results from the experiment, all samples are prepared in an identical manner as far as possible. All the unforeseen deviations were also noted at the time of preparing the samples to discuss unforeseen outcomes.

Chapter 4: Proposed methods are discussed in the chapter. The basic working procedures of the developed sensors to detect bleeding are discussed. The hardware architectures of the developed sensors are clearly explained. The design criteria of the sensors, architectural design, and the results are presented in this chapter as well. The limitations of the sensors and expected results are also discussed in the chapter.

Chapter 5: Methods of selecting the most significant features for the classifier models are discussed in this chapter

Chapter 6: Development of the machine learning models and algorithms related to the pre-processing of the data before feeding into the machine learning model are discussed in the chapter. The complexity analysis, performance of the model, and model's accuracy are also discussed.

Chapter 7: The chapter discusses the comparative analysis of all the methods by incorporating.

CONCLUSION:

In conclusion, this literature survey provides a comprehensive overview of current knowledge and advancements in the management of gastrointestinal bleeding. The key findings and insights from the reviewed literature can be summarized as follows:

Advancements in Diagnostic Modalities:

The literature highlights the evolving landscape of diagnostic tools for GI bleeding, including the role of advanced endoscopic techniques, capsule endoscopy, and radiological imaging modalities. These advancements have improved our ability to identify bleeding sources more accurately and expediently.

Risk Stratification and Prediction Models:

Various risk stratification scores and prediction models have been studied to guide clinical decision-making and resource allocation. The utilization of scores like the Rockall Score and Glasgow Blatchford Score has shown promise in identifying patients at higher risk of adverse outcomes.

Role of Early Intervention:

Early endoscopic intervention within recommended time frames has been consistently associated with improved outcomes, particularly in high-risk patients. This emphasizes the importance of prompt assessment and access to endoscopic services.

Pharmacological and Adjunctive Therapies:

The literature underscores the efficacy of pharmacological agents such as proton pump inhibitors (PPIs), tranexamic acid, and somatostatin analogs in certain cases of GI bleeding. Additionally, the use of interventional radiology and surgical techniques as adjuncts to endoscopic therapy has been explored in refractory cases.

Challenges and Areas for Improvement:

Despite advancements, challenges persist in the management of GI bleeding, including diagnostic uncertainties in cases of occult bleeding, resource limitations, and variability in transfusion practices. Addressing these challenges will require continued research and quality improvement initiatives.

Future Directions:

Moving forward, future research should focus on refining risk stratification tools, optimizing therapeutic algorithms, and exploring novel interventions for specific etiologies of GI bleeding. Furthermore, large-scale prospective studies are needed to validate emerging strategies and improve patient outcomes.

CHAPTER 3

AIM AND SCOPE OF THE PROJECT

3.1 MACHINE LEARNING MODELS AND THEIR PERFORMANCE EVALUATION

Dataset is taken as input to the classification methods followed by performance evaluation as depicted in Fig. 6.1. Four types of classification methods are used to analysis the results. The experiments are done by using Python and Scikit-learn library. The training process of a model is the process of feeding data into a neural network and letting it learn the patterns of the data by itself. The training process takes in the data and pulls out the best features of the dataset. During the training process for a supervised classification task, the network is passed both the input features and the response labels of the training data. However, during testing, the network is only fed with input features.

In the testing process, the learnt patterns of that network are tested. The features are passed to the network, and the network then predict the proper response labels. The data for the network is divided into training and testing sets. The output classifier or model can not be evaluated with the same training dataset since the it has already learnt the characteristics of that dataset during its training process. So, it would be extremely biased if it is being tested against the same dataset for further analysis.

Therefore, it is necessary to distinguish the training and the testing data from the dataset in order to train and evaluate the model. But during the development phase, it may not be always possible to have so many details. The obvious solution in such situation is to split the dataset into two sets, one for training and the other for testing; and it has to be done before starting the model training. It is also required to make sure splitting the data should be in a proper manner. In order to achieve that task, for this research, the whole datasets were divided into training and testing datasets. The testing datasets were kept fully separated. The training datasets had no influence of the testing datasets.

The models were trained in such a way that it could provide accurate validation results for the fully separated testing datasets. It is important to compare the performance of multiple machine learning algorithms consistently. The key to a fair comparison of machine learning algorithms is ensuring that each algorithm is evaluated in the same way on the same data. In order to ensure that, each algorithm will be evaluated on a consistent test harness.

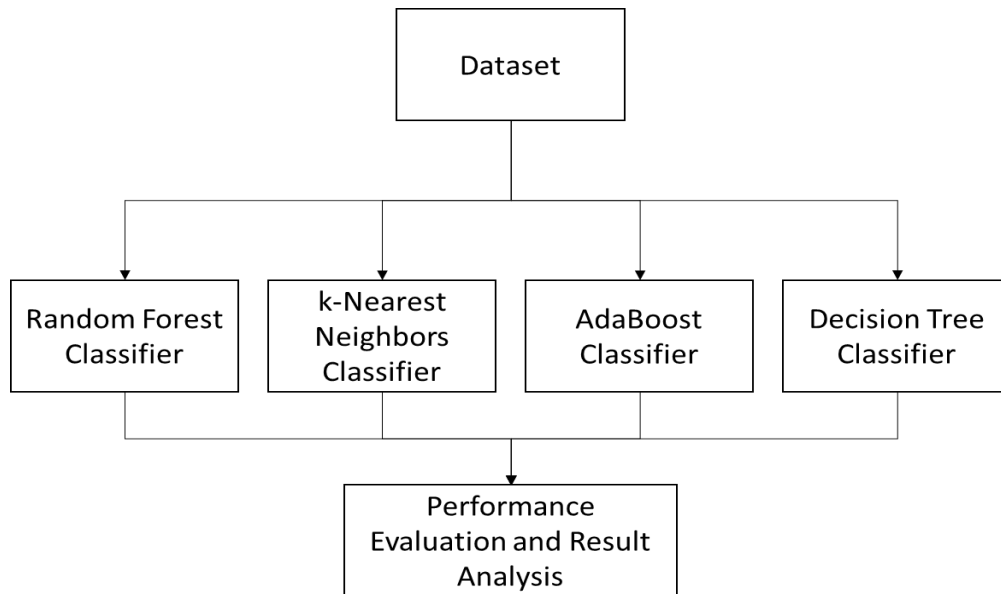


Figure 3.1: Proposed experimental framework

Four different algorithms were used for comparison in this research:

- k-Nearest Neighbours Classifier
- Random Forest Classifier
- Decision Tree Classifier

These four machine learning algorithms are very handy, popular and important, particularly for text analytics and general classification. Some of the algorithms are discussed below-

3.2 k-Nearest Neighbors Classifier

k-Nearest Neighbors (k-NN) is one of the best machine-learning algorithms that is very basic, flexible, easy to understand and scalable. It has succeeded in a large number of classification and regression problems, despite its simplicity. It is in the area of supervised learning and is widely applicable to the analysis of patterns, data mining, intrusion detection, economics, safety, political science, handwriting, video recognition, etc. It is appropriate for statistical problems of both classification and regression. It is primarily used in the industry for statistical classification problems, though.

It is an algorithm for non-parametrical and lazy learning. Non-parametric means for the underlying assumptions on data representation, there is no inference. In other words, the model structure is calculated from the dataset. In its training phase it uses the entire dataset. Whenever a prediction is made for an unseen data case, it scans for k-most like instances through the whole training data and eventually returns the decision with the most similar instance. It implies that when k is close to 1, the class label is given to the nearest neighbor. Nevertheless, if K is 5, the algorithms choose the next five most closely related data points and categories them according to groups represented by the corresponding five items, by a majority vote.

k-NN is often used in search applications where related objects are being searched, such as finding similar items. Algorithms say that object is one of them, if it is close to its neighbors. Like the same way, apple is most likely a fruit, for instance, when apple is more similar to peach, pear, and cherry (fruit) than monkey, cats or rats (animals).

3.2 Steps of k-Nearest Neighbors Classifier

The k-NN algorithm utilizes 'feature similarities' to determine the values in new datasets, ensuring the new data point will be given a value based on how well that correlates with the points in the training set. For developing or building a classifier, the process of data collection, preparation, and then testing is common in the entire machinery learning area. A dataset is necessary to implement every algorithm. Therefore, the training and the test data must be prepared during the first phase of k-NN. The algorithm's other steps can be explained as below-

- Select an integer number K of the nearest neighbour.
- Calculate the Euclidean distance of K number of neighbours between test data and each row of the training data.
- Take the K nearest neighbour's according to the calculated Euclidean distance and sort them in ascending order.
- Count the number of the data points in each category among these K neighbour's
- The category for which the neighbour's number is highest is applied to the new data points.

3.2.1 Random Forest Classifier

Random forest is a type of supervised, ensemble-based learning algorithm. Ensembled algorithms combine more than one same or different type of algorithms for the classification of object. There are many individual decision-making trees created on a randomly divided dataset. The collection of decision trees is also known as the forest. Every individual forest tree in a randomforest provides a class prediction and the class with the most votes becomes the final prediction of the model which is shown in Fig. 6.2.

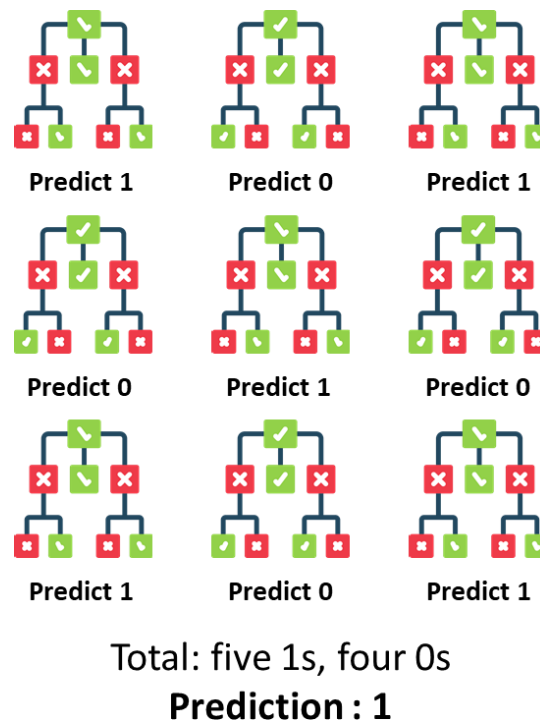


Figure 3.2: Random forest classifier's prediction

For classification and regression, which provides an estimation of the relations between a dependent variable and one or more independent variables, random forests can be used. It includes various applications, such as recommendation engines, classification of images and selection of features. It is ideal for classifying trustworthy lenders, detecting fraudulent activity and forecasting diseases. For almost every predictive issue (even non-linear ones), random forests classifier is a good choice. It is a rather new learning machine strategy that was developed in the 90's by Bell Labs.

Compared to other nonlinear classification algorithms, it is easier and more powerful. 90's by Bell Labs. Compared to other nonlinear classification algorithms, it is easier and more powerful.

3.2.2.1 Steps of Random Forest Classifier

Because of the number of decision-makers involved in the process, random forest classifier is recognized as an exceptionally precise and stable tool. The overfitting problem does not impact it since all forecasts were made on average, which cancels out the biases. The classifier works as follows-

- Pick random dataset samples.
- Build a sample decision tree and extract the outcome of each decision tree
- Take out a vote on each outcome that is predicted
- Pick the prediction outcome as the final prediction with the most votes.

3.2.3 Performance Matrices

Performance evaluation in a classification problem includes determining the classification performance of the system. A binary classifier predicts all data instances of a test dataset as either positive or negative. This classification (or prediction) produces four outcomes –

- True positive (TP): correct positive prediction
- False positive (FP): incorrect positive prediction
- True negative (TN): correct negative prediction
- False negative (FN): incorrect negative prediction

Sensitivity (SN) or recall (REC) is the possibility that representatives of the successful categories are appropriately identified. It is determined by dividing the right number of positive expectations by the total number of positive predictions. The highest sensitiveness is 1.0, while the worst response is 0.0 which also indicates how appropriate the model in determining positive predictions.

Probability of accurately identifying negative situations is specificity (SP). SP is calculated by dividing the amount of correct negative predictions by total negative numbers. It is also referred to as a true negative rate. The best feature is 1.0 and the worst 0.0 respectively. This explains how well the model can eliminate false alarms.

$$specificity (SP) = \frac{TN}{TN+FP} \quad (6.2)$$

Precision (PREC) decides the successful labeling quality. Precision quantifies the number of predictions in positive category that really belong to the positive class. The correct number of positive predictions divided by the overall positive predictions is considered as the precision. The highest accuracy is 1.0, while the worst is 0.0 and also indicates how many positive classifications are relevant.

$$precision (PREC) = \frac{TP}{TP+FP}$$

Accuracy (ACC) is the likelihood that accurately mark all positive and negative events. It is measured as the amount of all correct observations divided by the total dataset size. The highest accuracy is 1.0, while the worst is 0.0.

$$accuracy (ACC) = \frac{TP+TN}{TP+TN+FN+FP}$$

Almost all bleeding detection methods have utilized the metrics for system evaluation. However, all the methods calculate these measures using their specified classifier models.

3.3 Development and Analysis of Models for Experiment 1

In order to choose the best feature for the classifier model of the experiment 1, the collected sample data (10 blood samples and 25 non-blood samples) were observed carefully. From the observation, it appeared that the average and the ratio of the reflected light data from the two wavelengths might be used as features to separate the samples easily from the non-blood.

In the experiment, approximately 20 reflected sample data were collected for each of the 10 blood samples and 25 non-blood samples using both LED sets. After that, the ratio of the ARL of the two specific wavelength LEDs was calculated for both sets of LEDs. The cut-off point of the ratio for the 35 samples was determined by considering the mean value of the ratio of the 20 reflected sample data.

700nm and 625nm LED set were used mainly for the experiment as from Fig 3.2, it can be observed from the first LED set (475nm, 530nm) and second LED set (700, 625nm), the second LED set provides better separation between the ARL of ratio than the first LED set. So, it is wiser to choose the first LED set (700nm, 625nm) for the developed prototype to separate the blood and non-blood samples.

On the basis of the above experimental framework shown in Fig. 3.1, four classifier models were evaluated using python to carry out the binary classification task in which the blood samples were considered to be "1" while the non-blood samples were considered to be "0" in the classification.

All the models of the experimental framework used the above mentioned two features to train the blood detection model and calculate the probability scores. The models were compared based on different parameters of the models such as training accuracy, testing accuracy, precision scores, recall scores which are shown in Fig 3.3 to Fig. 3.6 respectively.

For Exp. 1, the k-NN classifier performs better than the other algorithms which is shown in Fig 3.4. The training accuracy for k-NN classifier was 92.50% which is lower than all the other classifiers but the test accuracy is higher than all the classifier which can be realized from the Fig.3.4.

Precision is another factor that indicates how many of the positively classified samples are relevant to the model. From Fig 3.5 it can be seen clearly that the k-NN classifier provides the best results out of all the algorithms.

The models' sensitivity or recall score is shown in Fig 3.6 which indicates how good the model is in detecting positive samples. k-NN provides a recall value of 83.33% which also seems higher or equivalent compared to the other algorithms.

All the performance matrices of the algorithms can also be visualized in Table 3.1. From the table, it is clear that the k-NN classifier provides the best results for test accuracy, precision, AUC matrices. So, it can be surely concluded that the k-NN is the best algorithm for classifying blood and non-blood samples for Exp.1m

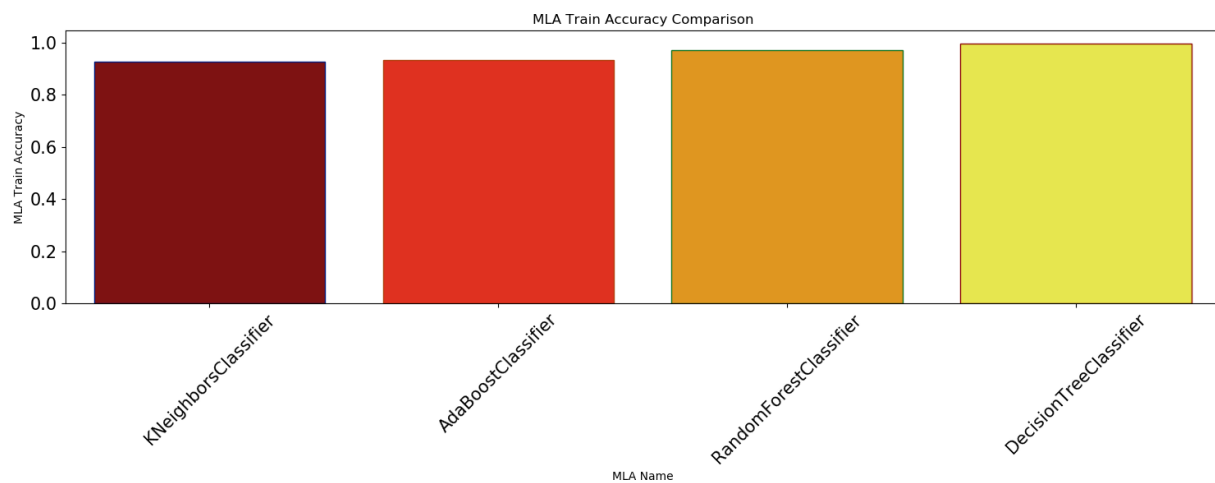


Figure 3.4: Machine learning algorithms' test accuracy comparison (Experiment 1)

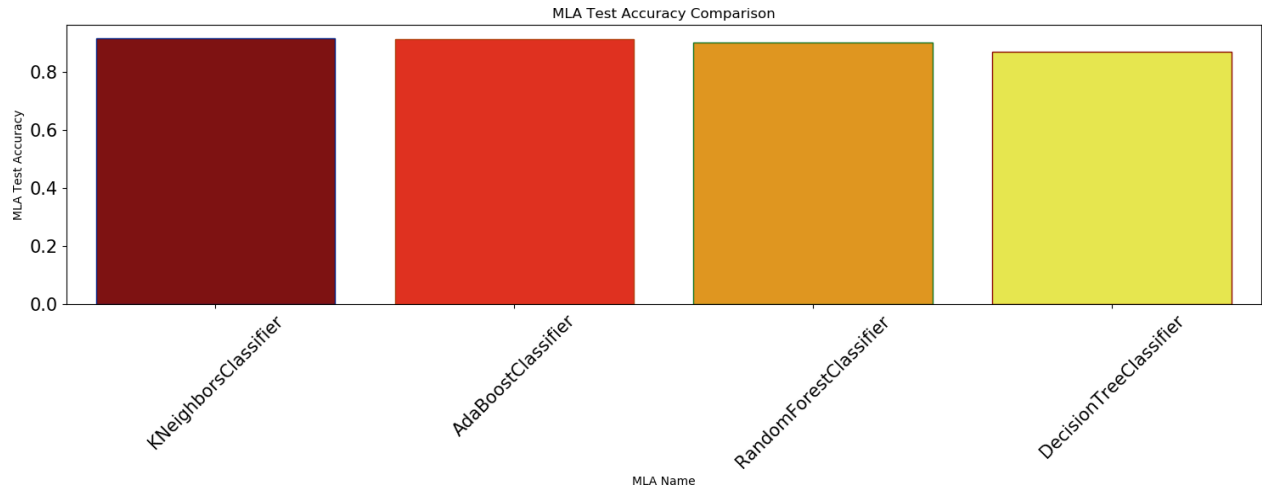


Figure 3.4: Machine learning algorithms' test accuracy comparison (Experiment 1)

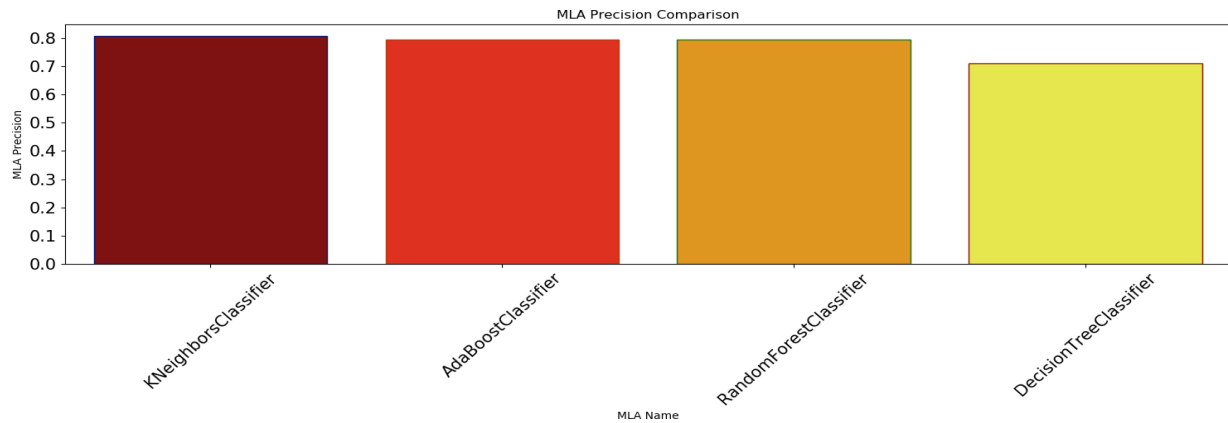


Figure 3.5: Machine learning algorithms' precision comparison (Experiment 1)

The samples were considered to be blood or non-blood samples based on the highprobability calculated by the trained model. From the initial Spectrophotometer experiment, it is found that the first set of LEDs with 700nm and 625nm performs better than the second set of LEDs with 475nm and 530nm.

So, in this experiment, 700nm to 625nm reflected value dataset was used to figure out the best result from the machine learning model. According to the analysis of four different models, the highest testing accuracy was found to be 91.54% for the k-NN classifier.

MLA Name	MLATrain Accuracy	MLA Test Accuracy	MLA Precision	MLA Recall	MLA AUC
K Neighbors Classifier	0.925	0.9154	0.8064	0.8333	0.8866
Ada Boost Classifier	0.9341	0.9115	0.7936	0.8333	0.8841
RandomForest Classifier	0.9727	0.8962	0.7894	0.750	0.8450
Decision Tree Classifier	0.9955	0.8692	0.7096	0.7333	0.8216

Table 3.1: Analysis of machine learning algorithms' performance using different Performance matrices for Exp. 1

The model predicts the blood samples from the non-blood samples with good accuracy but it fails to separate at some of the samples. The model mostly failed to separate the blood samples having a low dilution of less than 1-2% and some non-blood samples which had a strong color similar to blood with higher light absorption characteristics. The confusion matrix is very useful to understand the performance of any classifier. It gives information about predicted and actual values.

Here TP is the number of positive examples that are correctly classified, TN is the number of negative examples that are correctly classified, FN is the number of positive examples that are incorrectly classified as negative and FP is the number of negative examples that are incorrectly classified as positive. There are different types of performance matrices are used in this research (1) Overall Accuracy, (2) Specificity, (3) Recall, (4) Precision, (5) ROC curve (AUC). The specificity is the proportion of the TN and (TN+FP) and with the higher specificity fewer positive cases are labeled as negatives, so this ratio can be regarded as the percentage of negative cases correctly classified as belonging to the negative class. The proportion of cases that are TP for all the cases that are positive in the diagnostic tests (TP+FN) is called sensitivity. It ranges from 0 to 1 and an attribute that is perfectly correlated to the class provides a value of 1.

The confusion matrix is shown in Fig. 3.7 to describe the performance of the k-NN model on the test dataset. From the confusion matrix, it can be clearly understood that out of the 200 non-blood samples 188 samples are correctly predicted, and out of the 60 blood samples 50 samples are correctly predicted which gives an overall accuracy of 91.54%

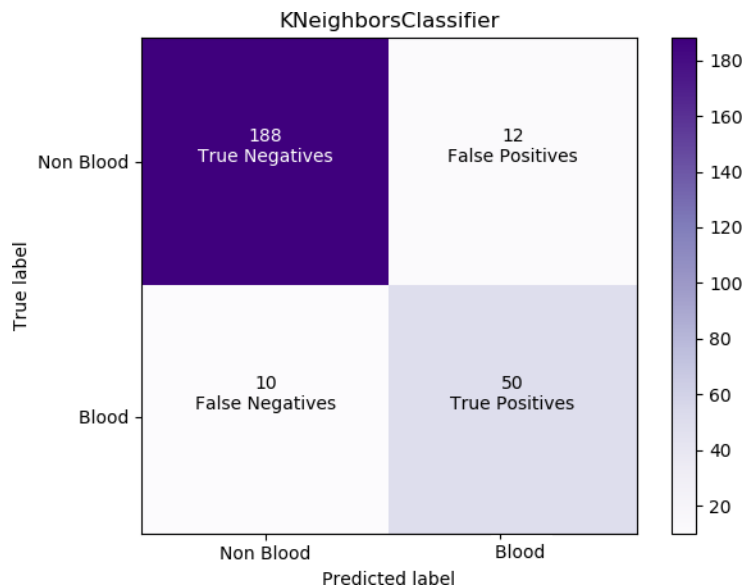


Figure 3.6: Confusion matrix of the k-NN classifier (Experiment 1)

Summary of Experiment 1:

Training data: 7 blood samples, 15 non-blood samples (20 data/sample)
 $7 \times 20 = 140$, $15 \times 20 = 300$. Total = 440 samples

Fully separated testing data: 3 blood samples, 10 non-blood samples (20 data/sample)

Blood = $3 \times 20 = 60$,

Non-blood = $10 \times 20 = 200$,

Total = 260 samples

k-NN Classifier's Performance Details:

Blood/Positive = 60 (True Pos = 50, False Neg = 10)

Non-blood/Negatives = 200 (True Neg = 188, False Pos = 12)
Test accuracy = 91.54%

3.4 Development and Analysis of Models for Experiment 2

The models for the second and third methods with the AS7262 and AS7263 modules are combined for the proper development of the classifier and only 3 most significant features out of the 12 features were selected. For each of the spectral wavelengths, 20 sample data were collected for the training. So, around 700 sample data (500 data values for 25 non-blood food color samples and 200 data values for 10 blood samples) were used for the training and testing.

According to Table 5.3, three features - 500nm, 550nm, and 610nm wavelength will be used for the development and analysis of the models based on the experimental framework shown in Fig. 3.1.

Four classifier models were evaluated using Python to carry out the binary classification task in which the blood samples were considered to be "1" while the non-blood samples were considered to be "0" in the classification. The models' training accuracy, testing accuracy, precision scores, recall scores are shown in Fig 3.9 to Fig. 3.11 respectively.

For the experiment 2, reflected light values were used as the features for developing the classifier model. Out of the four classifier models, k-NN classifier performs better than the other algorithms in the validation data. Fig 3.9 and Fig 3.10 indicate that k-NN provides a training accuracy of 97.95% and test accuracy of 89.23% which are higher than most of the algorithms.

Fig 3.11 indicates k-NN also provides higher precision value which is around 0.7857. This score indicates the model's positively classified predictions are very relevant to the actual value.

From Fig 3.12, it is clear that the k-NN classifier algorithm is very good at detecting positive values out of all the classifier algorithms. The overall summary of all the classifier models can be observed in Table 6.2.

So, it is clear that the k-NN algorithm is the best approach to differentiate the blood and non-blood samples for the experiment 2.

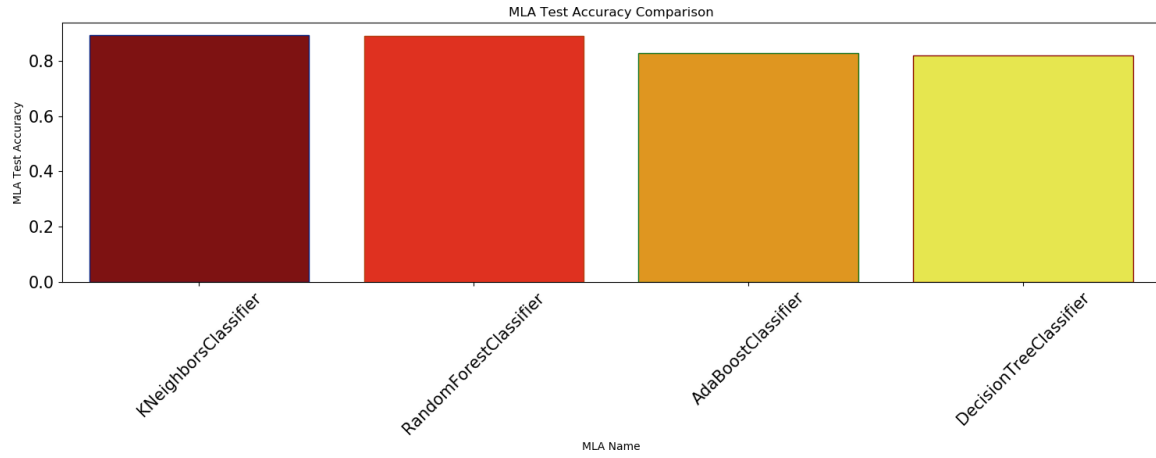


Figure 3.7: Machine learning algorithms' test accuracy comparison (Experiment 2)

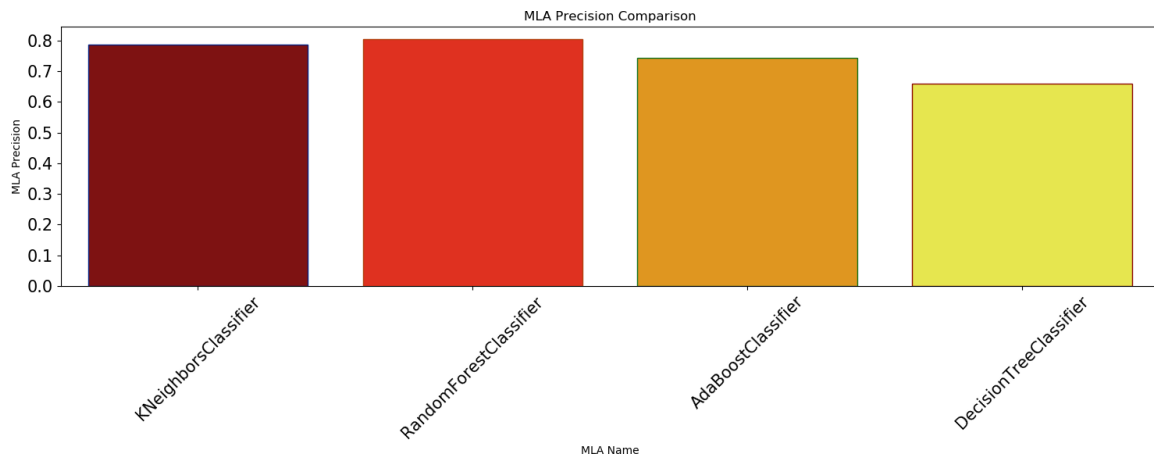


Figure 3.8: Machine learning algorithms' precision comparison (Experiment 2)

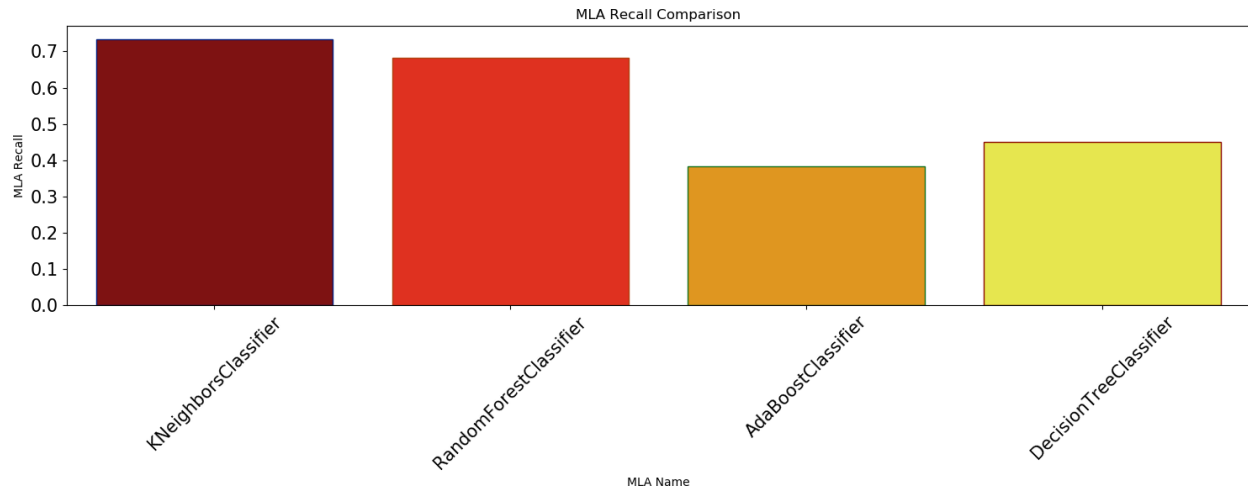


Figure 3.9: Machine learning algorithms' recall comparison (Experiment 2)

From Table 3.2, it can easily be seen that the k-NN classifier performed really well in separating the blood and non-blood samples with a testing accuracy of 89.23%.

Table 3.2: Analysis of machine learning algorithms performance using different performance

MLA Name	MLA Train Accuracy	MLA Test Accuracy	MLA Precision	MLA Recall	MLA AUC
KNNNeighborsClassifier	0.9795	0.8923	0.7857	0.7333	0.8366
RandomForestClassifier	1.0	0.8885	0.8039	0.6833	0.8166
AdaBoostClassifier	0.9977	0.8269	0.7419	0.3833	0.6716
DecisionTreeClassifier	1.0	0.8192	0.6585	0.45	0.69

The confusion matrix of the k-NN model is shown in Fig 3.13. From that figure, it can be understood clearly that, out of the 200 samples of non-blood samples 188 samples were correctly predicted and 12 samples were wrongly predicted.

On the other hand, for the 60 blood samples, all the samples were predicted correctly. So, the k-NN classifier model provides an accuracy of around 89.23%.

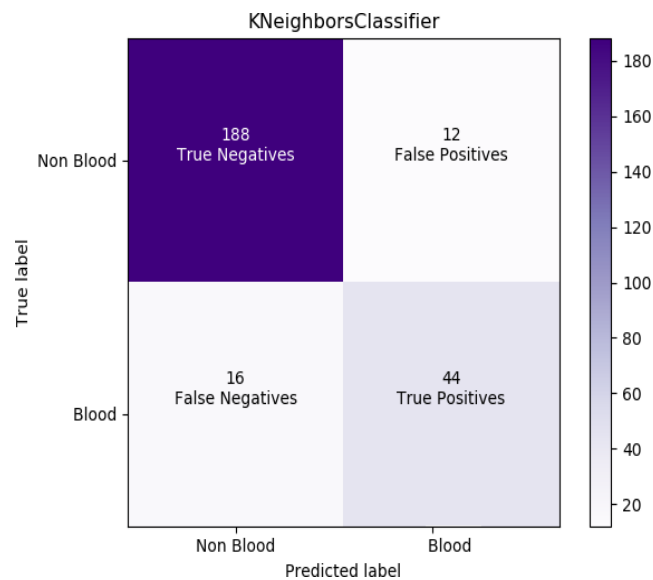


Figure 3.10: Confusion matrix of k-NN classifier (Experiment 2)

Summary of Experiment 2:

Training data: 7 blood samples, 15 non-blood samples (20 data/sample)

$7*20=140$, $15*20=300$. Total= 440 samples

Fully separated testing data: 3 blood samples, 10 non-blood samples (20 data/sample)

Blood= $3*20=60$,

Non-blood= $10*20=200$,

Total= 260 samples

k-NN Classifier's Performance Details:

Blood/Positive= 60 (True Pos=44, False Neg=16)

Non-blood/Negatives=200 (True Neg=188, False Pos=12)

Test accuracy=89.23%

3.5 Development and Analysis of Models for Experiment 3

In case of experiment 3, machine learning models are developed based on the only 3 most significant features (500nm, 550nm and 610nm). The difference between the experiment 2 and experiment 3 is basically with the dataset. In experiment 3, more blood and non-blood samples were added to represent the real experimental scenario by including pig's intestine with the existing dataset.

There were 32 non-blood samples and 22 blood samples in experiment 3 compared to the 25 non-blood samples and 10 blood samples in experiment 2. For each of the samples around 20 sample data were collected for the training. Three top most selected features- 500nm, 550nm, and 610nm wavelengths were used for the development and analysis of the four classifier models.

The k-NN classifier and decision tree classifier models perform better than the other two models. Fig 3.15 and Fig 3.16 indicate that k-NN classifier provides a training accuracy of 98.33% and test accuracy of 89.05% which are higher than the other algorithms. Fig 3.18 indicates that the k-NN classifier also provides a higher recall value of 0.8875 than the other classifiers.

The k-NN has also shown a higher AUC value of 0.8899 which indicates that it is good at separating the different classes. The overall summary of all the classifier models can be observed in Table 3.3. Therefore, it can be seen that the k-NN classifier is very efficient at differentiating the blood and non-blood samples using the 3 specified spectral wavelengths.

CHAPTER 4

SOFTWARE REQUIREMENTS

4.1 MATLAB

MATLAB, short for MATrix LABoratory, is a high-performance language for technical computing. It integrates computation, visualization, and programming in an easy-to-use environment where problems and solutions are expressed in familiar mathematical notation. Developed by MathWorks, MATLAB has become an indispensable tool in various fields such as engineering, physics, mathematics, finance, and even biology, for both academic and industrial applications.

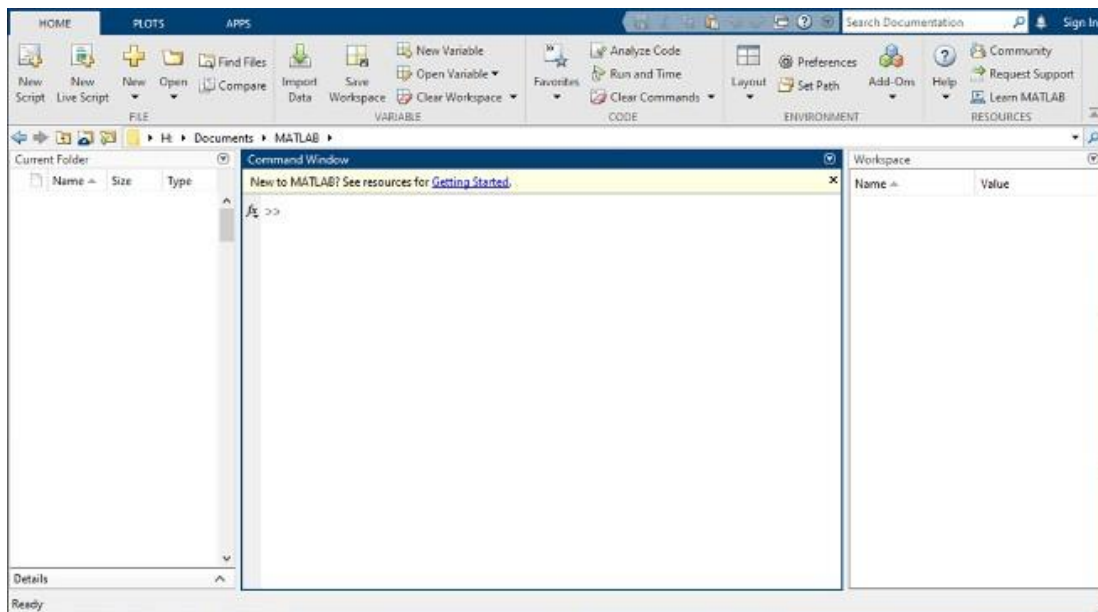


Figure 4.1 Matlab Home page

4.1.1 KEY FEATURES OF THE MATLAB :

The Numerical Computation: MATLAB excels at matrix operations, which are fundamental to many types of numerical computations. It supports various numerical functions including those for linear algebra, statistics, Fourier analysis, filtering, optimization, numerical integration, and solving ordinary differential equations.

Programming and Scripting: With its own programming language, MATLAB allows you to create scripts and functions, enabling the automation of repetitive tasks and the creation of custom algorithms.

Data Analysis and Visualization: MATLAB provides tools for data analysis and visualization. You can create plots and graphs to visualize data, tools for processing, cleaning, and analyzing large sets of data, and features for performing complex mathematical transformations and analyses

Modeling and Simulation: MATLAB is widely used for simulation in various fields. With its Simulink package, it provides a graphical editor, customizable block libraries, and solvers for modeling and simulating dynamic systems.

Application Development: MATLAB allows for the design of GUI (Graphical User Interface) applications. Through its GUIDE (GUI Development Environment) or App Designer, users can create interactive applications without being an expert in computer programming.

Toolboxes: MATLAB offers a wide range of toolboxes, which are comprehensive collections of MATLAB functions (M-files) that extend the MATLAB environment to solve particular classes of problems. Areas in which toolboxes are available include signal processing, control systems, neural networks, fuzzy logic, wavelets, simulation, and many others.

Integration with Other Languages and Hardware: MATLAB can be integrated with languages like C, C++, Java, and Python, allowing for the use of MATLAB algorithms within other programming environments. It also supports hardware integration for data acquisition, image processing, and instrument control.

Education: MATLAB is widely used in universities and colleges for teaching and research. Its simplicity and flexibility make it a valuable tool for students to learn numerical analysis, matrix computations, and programming.

4.2 MAIN COMPONENTS OF MATLAB

MATLAB Desktop Environment: The interactive environment includes tools (such as the Command Window, the Workspace Browser, and the Editor) that help in managing the files and variables and in debugging and developing MATLAB applications.

MATLAB Mathematical Function Library: This is a vast collection of computational algorithms ranging from basic functions like sum, sine, cosine, and complex arithmetic, to more sophisticated functions like matrix inverse, matrix eigenvalues, Bessel functions, and fast Fourier transforms.

MATLAB Language: It's a high-level matrix/array language with control flow statements, functions, data structures, input/output, and object-oriented programming features. MATLAB's language is specifically suited for vectorized operations, making it possible to perform complex computations quickly and with relatively little code compared to more traditional languages like C or Python.

Graphics System: MATLAB has extensive capabilities for displaying vectors and matrices as graphs, as well as annotating and printing these graphs. It includes high-level commands for two-dimensional and three-dimensional data visualization, image processing, animation, and presentation graphics.

MATLAB API (Application Program Interface): This allows users to write C and Fortran programs that interact with MATLAB. It includes facilities for calling routines from MATLAB (dynamic linking), calling MATLAB as a computational engine, and for reading and writing MAT-files.

4.2.1 WORKING OF MATLAB:

Execution: When you run a MATLAB command or script, the MATLAB engine performs the instructed operations. For compiled languages, code must be compiled before it is run; MATLAB, however, interprets your commands and scripts, executing instructions directly without the need for a separate compilation step. This makes it particularly suited for exploratory data analysis and prototyping.

Function-Based Operation: Much of MATLAB's functionality comes from its functions. Whether built-in, user-defined, or brought in through toolboxes, functions are the primary means by which tasks are performed. Users call these functions with appropriate inputs and then manipulate or visualize the outputs.

Scripting and Automation: MATLAB scripts (files containing sequences of MATLAB commands) automate repetitive tasks, combining computational and plotting commands to produce a comprehensive set of results on a given dataset or problem set.

Integration with External Software and Hardware: MATLAB integrates with external software through interfaces with languages like Python, Java, C, and C++, and it can control hardware such as cameras, motors, and sensors, facilitating complex experiments and data collection.

Execution Flow

Input: Data or commands are entered via the Command Window, a script, or a function.

Processing: MATLAB interprets the input, performing computations, function calls, or graphical operations as requested.

Output: Results are returned to the user, displayed in the Command Window, visualized through figures, or written to files.

MATLAB's design as an interactive environment, combined with its powerful computational and visualization capabilities, makes it a versatile tool for engineers, scientists, and mathematicians. Its ease of use, extensive library of functions, and ability to rapidly prototype.

4.3 DESCRIPTION OF PROPOSED MODEL

4.3.1. METHODOLOGY:

The application of a K-Nearest Neighbours (KNN) algorithm for detecting gastrointestinal (GI) bleeding or related stomach problems through machine learning involves several key steps. This method focuses on classification by identifying which category a new observation falls into, based on a dataset of observations whose categories are known. Here's how you might structure and implement such a process, step by step:

Step 1: Data Collection

Collect data relevant to GI bleeding, which could include patient demographics, symptoms, laboratory test results, and endoscopic images. Since KNN can work with both numerical and categorical data, your dataset could be a mix of both. For image data, you might first need to process the images into a feature vector that quantifies relevant aspects of the images (like color histograms, texture, or shapes).

Step 2: Data Preprocessing

Cleaning: Remove or impute missing values since KNN does not handle missing values well.

Normalization/Standardization: Scale numerical features because KNN is sensitive to the distances between data points.

Feature Extraction (for images): Convert images into a form that can be used for analysis, typically a vector of numerical features. Techniques like edge detection or more sophisticated methods like convolutional neural networks (CNNs) might be used to extract these features.

Encoding Categorical Variables: Convert categorical variables into a numerical format if any exist in your dataset.

Step 3: Feature Selection

Select the most relevant features to the problem of detecting GI bleeding. Irrelevant or redundant features can decrease the accuracy of KNN because they can distort the distance measurements the algorithm relies on.

Step 4: Choose the Value of K

The choice of K (the number of nearest neighbors to consider) is crucial. A too-small value makes the model sensitive to noise, whereas a too-large value might include points from other classes. Techniques like cross-validation can be used to find an optimal value for K.

Step 5: Distance Metric Selection

Decide on a distance metric (e.g., Euclidean, Manhattan, Minkowski) that determines how the "closeness" of data points is calculated. The choice of metric can significantly impact the performance of the KNN algorithm.

Step 6: Model Training

KNN is a lazy learning algorithm, meaning it does not build a model in the traditional sense. Instead, it memorizes the training dataset. Therefore, this step involves setting up the algorithm with the chosen K value and distance metric, and ensuring the training data is accessible.

Step 7: Prediction

To make a prediction for a new observation:

Calculate the distance between the new observation and all points in the training set. Identify the K closest points and tally the categories (labels) of these points. Assign the new observation to the category most common among its K nearest neighbours.

Step 8: Model Evaluation

Use metrics like accuracy, precision, recall, and the confusion matrix to evaluate how well your KNN model performs on a test dataset not seen by the model during the training phase.

Step 9: Parameter Tuning

Based on the performance on the test set, you might decide to adjust K, choose a different distance metric, or alter the feature set, and then reevaluate the model.

Implementation in MATLAB

In MATLAB, you can use the `fcknn` function from the Statistics and Machine Learning Toolbox to train a KNN classifier. Here's a basic example:

4.4 : STANDARDS

Standards for managing gastrointestinal (GI) bleeding typically involve a combination of clinical guidelines, protocols, and best practices established by medical societies and organizations. Here are some key standards commonly followed in the management of GI bleeding:

Recognition and Initial Assessment:

Prompt recognition of GI bleeding based on symptoms such as hematemesis (vomiting blood), melena (black, tarry stools), or hematochezia (fresh blood in stools).

Initial assessment of the patient's hemodynamic stability, including vital signs such as blood pressure, heart rate, and assessment of blood loss severity.

Risk Stratification:

Stratifying patients into high-risk and low-risk categories based on clinical factors such as age, comorbidities, vital signs, and presentation (e.g., Rockall Score or Glasgow Blatchford Score).

Diagnostic Evaluation:

Use of diagnostic modalities such as upper endoscopy (esophagogastroduodenoscopy, or EGD) and lower endoscopy (colonoscopy) to identify the source and severity of bleeding. Imaging studies like CT angiography or nuclear medicine scans in select cases.

Resuscitation and Supportive Care:

Initiation of resuscitative measures including intravenous fluids, blood products if needed, and possibly vasopressors in unstable patients. Monitoring and correction of coagulopathy if present.

Endoscopic Intervention:

Early endoscopy (within 24 hours) for high-risk patients to identify and potentially treat bleeding lesions (e.g., variceal band ligation, epinephrine injection, or thermal coagulation).

Pharmacological Therapy:

Use of pharmacological agents like proton pump inhibitors (PPIs) to reduce gastric acid secretion and promote ulcer healing. Antibiotic therapy for certain cases like suspected variceal bleeding.

Transfusion Thresholds:

Establishment of transfusion thresholds based on hemoglobin levels and patient's clinical status to guide blood transfusion.

Interventional Radiology and Surgery:

Interventional radiology procedures (e.g., embolization) or surgical intervention for refractory or severe bleeding not amenable to endoscopic therapy.

Follow-up and Secondary Prevention:

Close follow-up post-discharge to monitor for re-bleeding and ensure appropriate secondary prevention measures (e.g., *Helicobacter pylori* eradication, discontinuation of NSAIDs).

These standards are typically outlined and updated by organizations such as the American College of Gastroenterology (ACG), the American Society for Gastrointestinal Endoscopy (ASGE), and other regional or national societies focused on gastroenterology and digestive diseases. Adherence to these standards helps optimize outcomes and reduce complications associated with GI bleeding.

4.5 Constraints

The management of gastrointestinal (GI) bleeding involves several constraints and challenges that healthcare providers must navigate to ensure optimal patient care. These constraints can impact the diagnostic, therapeutic, and follow-up aspects of managing GI bleeding. Here are some common constraints:

Clinical Presentation Variability:

GI bleeding can present with a wide range of symptoms and severity, from subtle occult bleeding to life-threatening hemorrhage. The variability in presentation can make timely diagnosis and risk stratification challenging.

Diagnostic Uncertainty:

Identifying the exact source and cause of GI bleeding may be complex, especially in cases of obscure or intermittent bleeding. Diagnostic modalities like endoscopy may not always be readily available or feasible in urgent situations.

Hemodynamic Instability:

Patients with severe GI bleeding may present with hemodynamic instability requiring immediate resuscitation and intervention. Managing these unstable patients while awaiting diagnostic confirmation poses a significant challenge.

Resource Limitations:

Availability of specialized diagnostic tools (such as endoscopy), expertise (interventional radiology, surgical services), and blood products can vary based on the healthcare setting (e.g., rural hospitals vs. tertiary care centers).

Patient Factors:

Comorbidities, anticoagulant or antiplatelet use, and advanced age can complicate the management of GI bleeding and influence treatment decisions.

Therapeutic Options:

Not all bleeding lesions are amenable to endoscopic therapy, especially in cases of massive hemorrhage or lesions located in challenging anatomical locations.

Transfusion Thresholds:

Determining the appropriate transfusion threshold for blood products can be challenging due to variability in patient responses and risks associated with transfusion.

4.6 CODE:

Example Code

```
function varargout = Gastro_Intestinal_Tract_Detection(varargin)

%    GASTRO_INTESTINAL_TRACT_DETECTION    MATLAB    code    for
Gastro_Intestinal_Tract_Detection.fig

%    GASTRO_INTESTINAL_TRACT_DETECTION, by itself, creates a new
GASTRO_INTESTINAL_TRACT_DETECTION or raises the existing

%    singleton*.

%

%    H = GASTRO_INTESTINAL_TRACT_DETECTION returns the handle to a new
GASTRO_INTESTINAL_TRACT_DETECTION or the handle to

%    the existing singleton*.

%

%
GASTRO_INTESTINAL_TRACT_DETECTION('CALLBACK', hObject,eventData,handle
s,...) calls the local

%    function named CALLBACK in GASTRO_INTESTINAL_TRACT_DETECTION.M
with the given input arguments.
```

```

%
%   GASTRO_INTESTINAL_TRACT_DETECTION('Property','Value',...) creates a new
GASTRO_INTESTINAL_TRACT_DETECTION or raises the
%   existing singleton*. Starting from the left, property value pairs are
%   applied to the GUI before Gastro_Intestinal_Tract_Detection_OpeningFcn gets
called. An
%   unrecognized property name or invalid value makes property application
%   stop. All inputs are passed to Gastro_Intestinal_Tract_Detection_OpeningFcn via
varargin.
%
%   *See GUI Options on GUIDE's Tools menu. Choose "GUI allows only one
%   instance to run (singleton)".
%
% See also: GUIDE, GUIDATA, GUIHANDLES

% Edit the above text to modify the response to help Gastro_Intestinal_Tract_Detection

% Last Modified by GUIDE v2.5 27-Dec-2022 10:03:11

% Begin initialization code - DO NOT EDIT
gui_Singleton = 1;
gui_State = struct('gui_Name',    mfilename, ...
    'gui_Singleton', gui_Singleton, ...
    'gui_OpeningFcn', @Gastro_Intestinal_Tract_Detection_OpeningFcn, ...
    'gui_OutputFcn', @Gastro_Intestinal_Tract_Detection_OutputFcn, ...
    'gui_LayoutFcn', [] , ...
    'gui_Callback', []);
if nargin && ischar(varargin{1})
    gui_State.gui_Callback = str2func(varargin{1});

```

```

end

if nargin
    [varargout{1:nargout}] = gui_mainfcn(gui_State, varargin{:});
else
    gui_mainfcn(gui_State, varargin{:});
end

% End initialization code - DO NOT EDIT


% --- Executes just before Gastro_Intestinal_Tract_Detection is made visible.
function Gastro_Intestinal_Tract_Detection_OpeningFcn(hObject, eventdata, handles,
varargin)

% This function has no output args, see OutputFcn.
% hObject    handle to figure
% eventdata  reserved - to be defined in a future version of MATLAB
% handles     structure with handles and user data (see GUIDATA)
% varargin    command line arguments to Gastro_Intestinal_Tract_Detection (see
VARARGIN)


% Choose default command line output for Gastro_Intestinal_Tract_Detection
handles.output = hObject;
axes(handles.axes1); axis off
axes(handles.axes2); axis off
axes(handles.axes3); axis off
axes(handles.axes7); axis off
% axes(handles.axes5); axis off
% axes(handles.axes6); axis off
set(handles.edit1,'String',' ')

```

```

set(handles.edit2,'String',' ')
% set(handles.edit3,'String',' ')

% Update handles structure
guidata(hObject, handles);

% UIWAIT makes Gastro_Intestinal_Tract_Detection wait for user response (see
UIRESUME)
% uiwait(handles.figure1);

% --- Outputs from this function are returned to the command line.
function varargout = Gastro_Intestinal_Tract_Detection_OutputFcn(hObject, eventdata,
handles)
% varargout cell array for returning output args (see VARARGOUT);
% hObject handle to figure
% eventdata reserved - to be defined in a future version of MATLAB
% handles structure with handles and user data (see GUIDATA)

% Get default command line output from handles structure
varargout{1} = handles.output;

% --- Executes on button press in pushbutton1.
function pushbutton1_Callback(hObject, eventdata, handles)
% hObject handle to pushbutton1 (see GCBO)
% eventdata reserved - to be defined in a future version of MATLAB
% handles structure with handles and user data (see GUIDATA)
global seg_img;global skw;

```

```

[filename, pathname] = uigetfile({'.',''.bmp';'.jpg';'*.*gif'}, 'Pick a CD Image File');
I = imread([pathname,filename]);
axes(handles.axes1);
imshow(I);title('Input Image');
I2 = imresize(I,[300,400]);
I3=rgb2gray(I2);
axes(handles.axes2);imshow(I3);title('Gray Image');
I4 = imtophat(I3,strel('disk',15));
axes(handles.axes3); imshow(I4);title('TOPHAT');
I5 = histeq(I4);axes(handles.axes7);
imshow(I5);title('Histogram Equalization');

function edit3_Callback(hObject, eventdata, handles)
% hObject    handle to edit3 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Hints: get(hObject,'String') returns contents of edit3 as text
%        str2double(get(hObject,'String')) returns contents of edit3 as a double

% --- Executes during object creation, after setting all properties.
function edit3_CreateFcn(hObject, eventdata, handles)
% hObject    handle to edit3 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    empty - handles not created until after all CreateFcns called

% Hint: edit controls usually have a white background on Windows.

```

```
% See ISPC and COMPUTER.

if ispc && isequal(get(hObject,'BackgroundColor'),
get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor','white');
end
```

% --- Executes on button press in pushbutton2.

```
function pushbutton2_Callback(hObject, eventdata, handles)
```

```
% hObject handle to pushbutton2 (see GCBO)
```

```
% eventdata reserved - to be defined in a future version of MATLAB
```

```
% handles structure with handles and user data (see GUIDATA)
```

```
axes(handles.axes1); cla(handles.axes1); title(""); axis off
```

```
axes(handles.axes2); cla(handles.axes2); title(""); axis off
```

```
axes(handles.axes3); cla(handles.axes3); title(""); axis off
```

```
axes(handles.axes7); cla(handles.axes7); title(""); axis off
```

```
% axes(handles.axes5); cla(handles.axes5); title(""); axis off
```

```
% axes(handles.axes6); cla(handles.axes6); title(""); axis off
```

```
set(handles.edit4,'String','**')
```

```
set(handles.edit5,'String','**')
```

```
set(handles.edit6,'String','**')
```

```
set(handles.edit7,'String','**')
```

```
set(handles.edit8,'String','**')
```

```
set(handles.edit9,'String','**')
```

```
set(handles.edit10,'String','**')
```

```
set(handles.edit11,'String','**')
```

```
set(handles.edit1,'String','**')
```

```
set(handles.edit2,'String','**')
```

```

% --- Executes on button press in pushbutton3.
function pushbutton3_Callback(hObject, eventdata, handles)
% hObject    handle to pushbutton3 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)
close

function edit9_Callback(hObject, eventdata, handles)
% hObject    handle to edit9 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Hints: get(hObject,'String') returns contents of edit9 as text
%        str2double(get(hObject,'String')) returns contents of edit9 as a double

% --- Executes during object creation, after setting all properties.
function edit9_CreateFcn(hObject, eventdata, handles)
% hObject    handle to edit9 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    empty - handles not created until after all CreateFcns called

% Hint: edit controls usually have a white background on Windows.
%        See ISPC and COMPUTER.

```

```

if      ispc      &&      isequal(get(hObject,'BackgroundColor'),
get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor','white');
end

```

```

function edit10_Callback(hObject, eventdata, handles)
% hObject    handle to edit10 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Hints: get(hObject,'String') returns contents of edit10 as text
%        str2double(get(hObject,'String')) returns contents of edit10 as a double

```

CHAPTER 5

RESULTS AND ANALYSIS

Input Images:

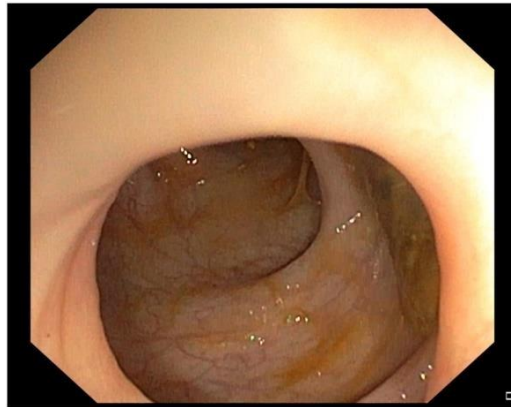


Fig 5.1: Unaffected Gastrointestinal Track

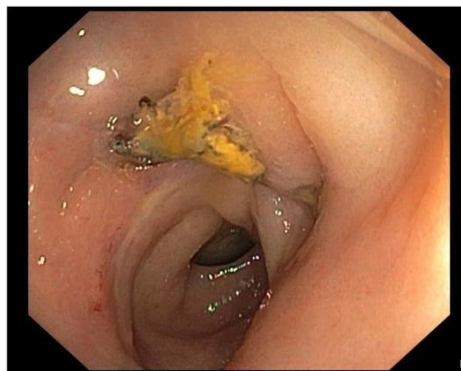


Fig 5.2: Affected Gastrointestinal Track



Fig 5.3 : Severely affected Gastrointestinal Track

Output:



Fig 5.4: Segmented Input Image

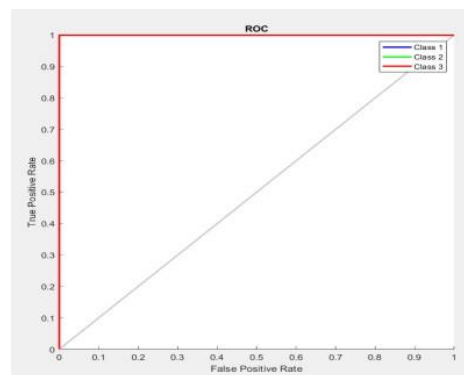


Fig 5.5 : TPR and FPR Graph

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1 CONCLUSION

The purpose of the research is to propose a method related to development of a bleeding detection sensor for the WCE system. Nevertheless, owing to similarity in blood components the same sensing and procedures could be used to classify human GI bleeding. Therefore, blood samples used in the analysis are not human blood but bovine hemoglobin. From the experimental setup with only two different wavelength LEDs (700nm and 625nm) provides a better result than the combined hardware setup using the AS7262 and AS7263 spectral sensors.

According to experiment 2 and experiment 3, it can be seen that the outcomes using food colors with and without pig's intestine provide an accuracy of 89.23% and 89.05% respectively which are quite similar. This kind of bleeding detection sensor system may be used with the existing WCE system by replacing the existing camera system which takes a longtime to detect bleeding.

The three spectral wavelengths- 500nm, 550nm, and 610nm of the AS7262 and AS7263 chips provide a better bleeding observation in both scenarios of with and without pig's intestine which may not be possible by an imaging sensor that only analyzes the color properties of the blood rather than the spectral properties of blood. Finally, it has been shown that the experiments with AS7262 and AS7263 sensors provide an overall accuracy of around 89% which could solve the problem of bleeding detection in all scenarios. Though the k-NN model is not good at predicting blood samples of 5% or lower concentrations, it has shown great efficiency and improved performance compared to the other existing methods.

6.2 FUTURE WORK

In this section, some recommendations have been provided to improve the design to detect the human GI bleeding which was beyond the scope of the thesis.

The experiments carried out in this analysis, take place in a controlled environment. In spite of some of the experiments were done with real pig's intestine, the results might be slightly different in real scenarios. Thus in-vivo sample testing with sensors is needed to confirm that the proposed sensors and the corresponding operating mode can be used in a living body environment.

The sensor, processor, transmission modules and power modules are becoming smaller and more efficient day by day. Therefore, several sensors might be combined into the endoscopic system for higher accuracy with more analytics.

The scale of the proposed sensors is slightly greater than that of capsule devices available on the market. It needs to develop technologies further to limit the size to a minimum.

One important point in miniaturizing the system is to design an IC which will combine all modules into a single integrated die. Thus, it would take less space and consume less power. In addition to the current features, other features like pH level, glucose level, etc., could be incorporated to detect GI tract abnormalities.

If there could have a triggering feature in the capsule which would change the camera's frame rate or wake up the capsule from power saver mode, then it could significantly save power consumption. In addition, there could be some research on getting the accurate position of the WCE capsule which will provide the exact bleeding location inside the body when bleeding is detected by the sensors

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