**Decoding Diabetes: Unconventional Indicators for**

**Diabetic Diagnosis**

**R24\_120**

**Sangavi.G - IT21069772**

**BSc (Hons) in Information Technology Specializing in Information Technology**

**Department of Information Technology**

**Sri Lanka Institute of Information Technology Sri Lanka**

**October 2023**

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# **Declaration page of the candidate & supervisor**

I, Sangavi Gnanasegaram, hereby declare that this research titled "Decoding Diabetes: The idea for the paper is titled “Unconventional Indicators for Diabetic Diagnosis” and the subtopic “Diabetes Detection Using Neck Images” is also a topic of my own creation. This work has been completed under the guidance of Wishalya Tissera and using suitable ethical practice and regulation for research. The information contained in this report has not been entered in this or in any other application for any degree or other academic qualification at any other institution.

I declare that all knowledge used in this research study has been cited and acknowledged as needed. Any support that has immensely contributed to the research is described and acknowledged.

Signature Data

The above candidate has carried out research for the bachelor’s degree dissertation under my supervision.

Signature of the supervisor: …......................... Date: …..........................

# **Abstract**

Diabetes is on the rise throughout the world and people are being diagnosed through such routine procedures as blood glucose testing. This research explores the possibility of utilizing neck girth and neck images as out-of-orneriness prediction parameters for diagnosis of diabetes militates. The study involved the use of a dataset of neck images where images were taken from subjects using smartphone camera, and images were labelled according to a doctor’s diagnosis leading to the formation of a binary classification set. The image preprocessing included the resizing of images to at most 416×416 pixels, and scaling normalization of the image pixel values, and the application of data augmentation techniques including rotation and scaling. Object detection and classification were achieved with the help of YOLOv8 model which was applied to define the existence of diabetes related patterns in neck images. The interpretation of the model was done on the annotated dataset in Google Colab under the environment of Tesla T4 GPU, Python 3.10.12, NVIDIA driver 535.104.05, and CUDA 12.2. In training process, much attention was paid to which sort of hyper parameters like learning rate, batch size and number of epochs to tune. The performance of used models was assessed by indicators that includes accuracy, precision, recall, and F1-score. The findings substantiate the possibility to apply the analyzed neck images to diagnose diabetes and avoid invasive and expensive diagnostic methods.

# **Acknowledgement**

I would like to extend my biggest appreciation to my supervisor, Wishalya Tissera, for their constant encouragement and assistance as well as comments on the research. They have provided their profound guidance and support in the management and the execution of this study.

I also want to thank all the participants who agreed to disclose their neck images and health information for this study. Extra thanks go to the technical support team for the computational part – especially had been setting up the Google Colab environment with the right meeting specifications.

In addition, all my family and friends whose encouragement even during the most challenging period of this research cannot be overemphasized. Last but not the least, I am grateful to all the people who in one way or the other have contributed to the preparation of the study.

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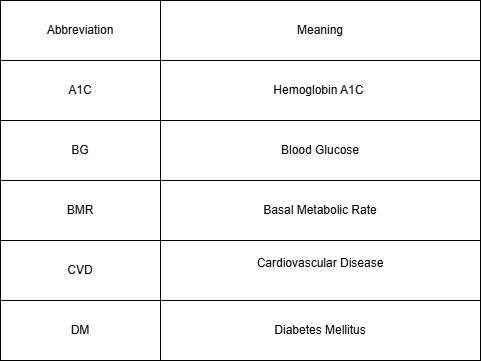
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# **List of abbreviation**



# **1.0. Introduction pages**

Diabetes is a long-standing illness with elevated blood sugar levels, which are mainly caused by the body not efficiently using insulin or producing enough of it. Diabetes is ranked as a major problem affecting human health standards worldwide and resulting in the worsening of dangerous consequences that threaten people’s lives, including heart diseases, neuritis, retinitis, and chronic renal failure. The traditionally utilized diabetes diagnostic techniques are dominated by blood tests such as fasting blood glucose, oral glucose tolerance, and HbA1c. Although techniques provide good results, they involve invasive procedures, specific apparatuses, and Clinical visits that discourage early and frequent screenings [1].

Due to the shortcomings that are inherent with conventional diagnostic techniques, there is growing research on identification of noninvasive and cheap diagnostic approaches to diabetes especially in developing nations. Relatedly, in the past few years, various abnormal peripheral measures and new screening tests from retinal image analysis to voice examinations have been suggested. These approaches seek to afford, fast and accurate diagnostic tools which may enhance better diagnosis and management of diabetes.

In this research, neck images are employed for diagnosing diabetes, and this approach has not been used before. Some cross sectional studies have shown that head neck circumference and some visual characteristics of neck can help predict the possibility of metabolic diseases including diabetes [2]. With the help of the computer vision, and machine learning, particularly YOLOv8, this research seeks to compare the early non-harmful diagnosis of diabetes with the neck images.

## **1.1. Background and Significance**

Diabetes has now become a global health issue and knowledge shows that over 537 million adults have diabetes as per the year 2021. It is projected to increase further in upcoming years to decades putting a lot of stress on the global health care system. There is nothing as vital as early diagnosis of diabetes because they do not only lead to other illnesses but also cause complications. However, traditional diagnostic methods encountered problems such as the need for qualified personnel, blood sampling and the cost of laboratory tests, which could deter people especially from the less developed world as they maybe too expensive.

Considering non-invasive solutions, for instance, taking the measurements of a patient’s body and analyzing images has raised many concerns. Thus, using neck circumference as a marker for insulin resistance and other related metabolic disorders have been acknowledged. The reasoning is based on the assumption that central obesity is characterized by subcutaneous fat deposit in the neck area, which is considered precursor of type 2 diabetes [3].

The present research suggests a new diagnostic strategy based on computer vision and analysis of neck images in an attempt to pinpoint diabetes-associated signs. Implementation of the YOLOv8 model, an advanced object detection algorithm can help perform an automated analysis of an image, and could be a quick and simple way to screen for diabetes. This approach can greatly benefit diabetes screening should the innovation be deemed efficient since the normal diagnostic methods are not easily available in the rural areas or parts of the developing world.

The importance of this study is in an opportunity to develop a differential diagnostic that would be more effective from the invasive one and can be implemented at the large scale at the low cost. To achieve this, the current research proposes to merge image-based and machine learning analysis with an interest to bring conventional approaches of identifying diseases and disorders, and modern technology into healthcare solutions. The publication may open the door to the subsequent studies of other unconventional indicators of diseases’ diagnosis and creation of efficient methods for preliminary health check. As of 2021. The number is expected to rise significantly in the coming decades, placing immense pressure on healthcare systems worldwide. Early diagnosis is critical for preventing the progression of diabetes and minimizing its associated complications. However, traditional diagnostic methods face several challenges, including the requirement for trained personnel, the invasiveness of blood sampling, and the cost of laboratory tests, which may be prohibitive for many individuals, particularly in low-income regions.

Exploring non-invasive approaches, such as using body measurements and image-based analysis, has become an area of significant interest [4]. Neck circumference, in particular, has been recognized as a potential marker for insulin resistance and other metabolic abnormalities associated with diabetes. The rationale is that excess fat accumulation around the neck region is often linked to central obesity, which is a known risk factor for type 2 diabetes.

This study proposes a novel diagnostic approach by employing computer vision techniques to analyze neck images and detect diabetes-related patterns. The use of the YOLOv8 model, a state-of-the-art object detection algorithm, enables automated image analysis, potentially offering a rapid and accessible screening tool for diabetes. If proven effective, this approach could significantly enhance diabetes screening, especially in remote areas and resource-constrained settings where traditional diagnostic methods are less accessible.

The significance of this research lies in its potential to provide an alternative diagnostic solution that is not only non-invasive but also cost-effective and convenient for large-scale implementation. By integrating image-based analysis with machine learning techniques, the study aims to bridge the gap between conventional medical diagnostics and modern technology-driven healthcare solutions. The findings could pave the way for further research on unconventional diagnostic indicators and the development of health screening tools.

## **1.2. Research Objectives**

The main hypothesis of this study is therefore to examine the probability and effectiveness of neck images as a diagnostic modality for the disease diabetes. Specifically, the study aims to:

1. Evaluate the relationship between neck circumference and diabetes diagnosis: Determine whether using size of the neck measured by its girth, or other specific characteristics extracted from photographs of neck, should be considered and used as …diabetes indicators.

2. Develop a machine learning model for diabetes detection using neck images: Here we propose the YOLOv8 a computer vision approach to identifying whether the neck diagram has patterns of diabetes present.

3. Optimize the model's performance through preprocessing and hyper parameter tuning: These will increase the result of the new model through the training improvement like the image resize, normalize and augmentation to get the result of the model and also the hyper parameter tuning of the model which is include learning rate, batch size and the number of epoch.

4. Validate the model using appropriate performance metrics: On the basis of these evaluation factors, it is possible to check the reliability of the presented model as a tool of diabetes detection by calculating its accuracy, precision, recall, F1 score.

5. Explore the potential for a non-invasive, cost-effective diagnostic alternative: It is possible to consider a scenario of using the trained model for screening many subjects in the areas where performing complex venipuncture diagnostics is challenging.

## **1.3. Scope of the Research**

This study focuses mainly on developing a method of screening for diabetes through images of the neck area. The scope of the study includes the following key aspects:

1. Dataset Collection: The research will also use a dataset of neck images captured from the participants with the use of android phones’ cameras. These pictures will be then labelled into the medical experts by diagnosing their conditions to predetermined diabetes; The result of which is that the actually obtained dataset comprises of two classes of data, which are Diabetes positive and Diabetes negative.

2. Image Preprocessing: During the study the collected neck images will be preprocessed to fit the required format as well as enhance the model performance. This includes resizing the images to a size of 416 x 416, normalizing the pixel as well as using data augmentation such as rotation and scaling.

3. Machine Learning Model Development: In the course of the research, YOLOv8 model from Ultralytics tool will be adopted mainly for its efficiency in the implementation of the object detection and classification. The model will be developed as well as tested in Google Colab ; more specifically; one of the main aims of the model will be to seek the highest hyper parameters through tuning within the model.

4. Evaluation and Validation: In the case of a dataset that will be used to evaluate the effectiveness of the trained model concerning diagnosis of diabetes; it is probable to calculate numerous factors such as accuracy, precision, recall and F1-score. This research will also analyses the performance of the model under condition of low or high image quality or with participants of certain age or gender.

5. Limitations and Challenges: The follow analytic limitations will also be addressed in the study; fluctuations found on neck images, demographic disparities such as age, gender, type of BMI other populations may not be included in the model’s global relevance.

## **1.4. Methodology Overview**

The technique applied in this research is data gathering process, image pre-processing, constructing machine learning model, and model evaluation. The steps are as follows:

* Data Collection: The study begins through collecting neck images from participants in order to construct a dataset by using the smartphone cameras. The images are accompanied by details about diagnosis of diabetes leading to a binary classification dataset; diabetes-positive or diabetes-negative. Participants consent has been obtained and all data collection procedures respects ethic process.
* Image Preprocessing: Some image preprocessing steps are carried out before doing the analysis as follows;

1. Resizing: All images are resized to 416×416 pixels to standard the input for the machine learning model too substantially.

2. Normalization: Pixels values are normalized so that the values are within the range of 0 and 1 in order to achieve the same scale for all the images.

3. Data Augmentation: Techniques such as rotation of images, scale and image flipping that are used with an aim of increasing the range of the training set and thus improve the generalization ability.

Machine Learning Model Development: The project use the YOLOv8 model which is likely the most current algorithm in the area of object identification and classification to process preprocessed neck images’ This work sets and use the model structure for determining the binary results in either a diabetes positive or negativity. Further parameters such as learning rate, batch sizes and number of epochs used to train the model is adjusted. The training is done in Google Colab with the environment including a Tesla T4 GPU.

Data Collection: The study initiates by capturing a dataset that has images of participants’ necks taken using Smartphone cameras. The images are linked to participants’ medical records showing whether the individuals have diabetes or not, thus generating binary classification data set – diabetes-positive and diabetes-negative. Any data from questionnaire responses is collected in a way that meets the ethical protocol to gain participant consent and observe their anonymity.

The YOLOv8 model by NVIDIA is adopted on the Google Colab platform for image preprocessing, resizing of the images, scaling of the image pixels and data augmentation. The model is trained and tested in the binary classification setup where it has to correctly segregate between positive diabetes and negative diabetes. Other aspects such as, learning rate, batch size, and number of epochs that are predetermined are readjusted for efficiency. The training process makes the possibility to have data divers and make the model have the generalization capability.

Model Evaluation: The trained model uses a test-set that was not used in the training processor Accuracy, precision, recall, F1-score are used to evaluate the proposed framework performance for diabetes detection’s Other cross-validation can also be applied in order to check the credibility of the model and its applicability to different data sets. Participants using smartphone cameras. The images are accompanied by medical records indicating whether the participants have been diagnosed with diabetes, creating a binary classification dataset (diabetes-positive and diabetes-negative). All data is collected in compliance with ethical guidelines, ensuring participant consent and anonymity.

NVIDIA's YOLOv8 machine learning model is used in a Google Colab environment for image preprocessing, resizing, normalization, and data augmentation. The model is configured for binary classification, distinguishing between diabetes-positive and diabetes-negative cases. Hyper parameters like learning rate, batch size, and training epochs are fine-tuned for optimal performance. The training process ensures data diversity and generalization capabilities.

Model Evaluation: The trained model is evaluated using a test set that was not involved in the training process:

* Performance metrics such as accuracy, precision, recall, and F1-score are calculated to assess the model's effectiveness in detecting diabetes.
* Cross-validation techniques may also be employed to ensure the robustness and generalizability of the model.

Result Analysis and Interpretation: The findings are discussed with a view to arriving at the possibility of using images of necks as means of diagnosing diabetes. The study also focuses on possible influences on the model, which include image quality and the participants.

Deployment Considerations: The study also fills the existing gap on the applicability of the model in practical contexts such as mobile application and telemedicine services.

## **1.5. Literature Review**

In the literature review, attention is paid to presenting the current knowledge regarding diabetes diagnostics, the non-traditional approaches to identify the disease, and application of computer vision in medicine.

## Diabetes Detection and Traditional Diagnostic Methods

Diabetes mellitus broadly known as diabetes, is a persistent illness that can be described as an increased level of glucose in the bloodstream because the body is unable to produce adequate insulin or inadequately use the insulin that is produced. This is one of the most common chronic conditions in the global health space, with millions of sufferers, and end-stage complications including heart disease, renal failure, blindness and neuropathy among others, where the condition is left poorly managed or untreated. One should note that early diagnosis and treatment of the conditions is essential to management and enhancing the experiences of those involved [5].

Traditional Diagnostic Methods: Blood-Based Tests

Traditional approaches for diagnosing diabetes primarily involve blood tests and are regarded as best practices founded on the credibility of the technique. The most commonly used blood tests for diabetes diagnosis include:

1. Fasting Blood Glucose Test (FBG):

Fasting blood sugar test evaluates the amount of glucose in the blood after the patient has had no food for at least 8 hours. As fasting blood glucose provides the first step before diagnosing diabetes mellitus, it has widespread usage as a screening test. Conventional diagnosis of diabetes is based on fasting blood glucose of 7.0 mmol/L or more or random blood glucose of 11.1 mmol/L or more or a post-load glucose of 7.8 mmol/L or more with a knowledge level of 7 or more. This test is quite accurate; however, it involves a fast, which can be cumbersome to some people, and does not pick out glucose irregularities which may only occur after a meal.

2. Oral Glucose Tolerance Test (OGTT)

OGTT determines the ability of the body to regulate glucose by evaluating the level of glucose in blood prior to and after taking a Cocktail of glucose. It can also be used to screen and diagnose gestational diabetes in pregnant women or back up a diagnosis of diabetes if your fasting blood glucose level is only slightly elevated. A solution with the quantity of glucose is taken by the individual and the food intake is evaluated at special periods; usually at 2-hour intervals [6]. A blood glucose level of 200 mg/dl (11.1 MMOL/L) and above at 2 hours is categorically conclusive of diabetes. While OGTT offered a tremendous sensitivity in diagnosing diabetes, it was equally more time-consuming as it needs several blood sampling and prolonged observation time.

3. Glycated Hemoglobin (HbA1c) Test

The HbA1c test gives the average of the patient’s blood sugar levels for the past two to three months through the amount of the hemoglobin in the blood that has been gyrated. Diabetes is diagnosed when the patient’s HbA1c level is above or equal to 6.5%. It does not have to be done on an empty stomach and is valuable in tracking chronic glycemic control. Nevertheless, the presence of hemoglobin variants, anemia, or recent blood transfusion influences the reliability of the outcomes.

Although these traditional diagnostic techniques for diabetes are essential in diagnosing patients, they still have some drawbacks that need the development of a new way of diagnosing it. For example:

Cost and Accessibility: Blood-based tests in particular need clinical environment and specific equipment and personnel to perform it. This becomes a challenge when seeking a diagnosis in a low health care setting or in the rural areas because there are few health centers [7]. The cost of such tests may also be very high and this does apply especially for those patients who require constant monitoring.

It is painful since it involves a penetration of the patient’s skin, especially in children and or any person who may be scared of needles.

Extensive literature is created by reviewing the literature on possible diabetes detection, features other than conventional diagnostic markers, and computer vision application in the health care.

Diabetes Detection and Traditional Diagnosis

Diabetes mellitus is called simply diabetes; is a long-term illness associated with high levels of glucose in the blood due to insufficient insulin production or inadequate use of insulin. Affecting millions of people and in turn causes life threatening complications like heart disease, kidney failure, loss of vision and nerve damage if well treated of poorly controlled. These complications are best prevented and controlled when they are detected early and thus it is important if those affected are hospitalized early.

Traditional Diagnostic Methods: Blood-Based Tests

Traditionally, the diagnostic methods for diabetes consist of blood tests, which are preferred, because they are more effective in terms of efficacy and specificity [8]. The most commonly used blood tests for diabetes diagnosis include:

1. Fasting Blood Glucose Test (FBG)

The fasting blood glucose test is the level of glucose in the blood after an individual has avoided food for at least 8 hours. Measurements are simplified and only require calculation of fasting blood glucose levels, hence, most insurance organizations use it as the first step of testing. Based on the above, the diagnostic criteria for diabetes is usually set at fasting plasma glucose of 7.0 mmol/L or more or a value of 7.0 mmol/L or higher 2 hours after ingestion of the glucose beverage. This test is accurate, although it entails fasting, which may not suit certain people, and will not detect glucose irregularities that arise only after eating.

2. Breath Analysis

Breath tests for a diabetes diagnosis apply the principle to detect VOCs in the breath that are related to the metabolic shifts of diabetes. For example, acetone, which is a VOC, rises in such individuals’ breath if they have poorly managed diabetes [9]. The possibility of developing Breath analysis devices or Breathalyzer for diabetes cases could be rapid and noninvasive. Despite the fact that this technology has not been widely applied in clinical diagnosis, further studies are improving the methods for breath-based detection and increasing both sensitivity and specificity values.

3. Retinal Image Analysis

Diabetes mellitus has been shown to affect the eyes whereby the physician can identify the condition through retinal imaging such as diabetic retinopathy. Modern technologies involving computer vision and artificial intelligence have reached the level at which image recognition of the retinal layer permits the diagnosis of diabetic tissue damage before symptoms of retinopathy develop. While no study of retinal imaging can be directly classified in the conventional sense as diagnosing diabetes, the approach is potentially valuable as a screening tool, especially on high risk candidates.

4. Skin Analysis Using Near-Infrared (NIR) Spectroscopy

Biochemical characterization based on NIR spectroscopy employs light absorbance in skin tissues to determine the corresponding metabolic biomarkers for diabetes conditions. It builds on the fact that light-based analysis is an intrusion-free way of identifying the levels of glucose or other diabetes indicators in the skin. Although NIR spectroscopy is not proven yet for its practical use, it is expected that the method for diabetes screening could be portable and easy to use.

5. Voice Analysis

The Acoustics of voice is relatively new discipline which seeks to study deviation from normal voice parameters and examine it for symptoms of various diseases like diabetes. The hypothesis is that diabetes may well impact the autonomic nervous system together with muscles that could make changes to vocalization [10]. While the development of this type of application is still in its early stages, it may produce diagnostic applications included in a smartphone or some other portable device.

**The Transition to Other Forms of Detection in the Early Stages**

Diabetes incidence is on the rise around the world, so a search for a non-invasive, inexpensive test that can be used as part of a screening programmer continues. This must be done to check the disease in the right stage so that the patient can be adequately managed without complications. There is a constant pressure to make differential diagnostic methods adaptable to everyday practice without demanding recurrent clinical visits due to advances in digital health, artificial intelligence, and wearable technology.

This research also follows with the general move to minimize invasive procedures by analyzing neck images’ possibilities to identify diabetes. Anthropometric measurement of neck circumference which reflects adiposity is related to metabolic risk factors including insulin resistance. Automating and learning from images of neck is a new way to assess the risk of developing diabetes without having to use an invasive procedure that requires specialized equipment or tools, but a technology everyone has in their pocket today – smartphone [11]. This approach is designed to make diabetes screening more accessible for people who would otherwise cannot visit a health facility due to various issues through using computer vision.

**Neck Circumference as an Electro Marker for Diabetes**

Neck circumference as an anthropometric measure has lately received growing interest due to its possible relationship with diabetes and other metabolic diseases. Originally, the risks associated with obesity have been estimated using indices including BMI, circumferences, and WTR. But there has been mounting research information showing that neck circumference could be equally useful in the estimation of metabolic disorders such as type 2 diabetes since neck adiposity is positively related to central obesity and insulin resistance.

**Neck Circumference and Central Obesity**

The audit showing fat build-up around the abdominal region is linked with metabolic diseases including type-2 diabetes and cardiovascular illnesses. It is related to insulin resistance – a condition in which the cells in the body do not respond effectively to the hormone insulin and blood glucose rises. Although abdominal adiposity is usually adopted as the main index of obesity from the standpoint of health risks [12], neck girth can be safely considered to be an important index in parallel with it.

Studies have thus indicated that neck circumference has a strong positive relationship with central obesity. The increase in neck circumference measurements has been linked with increased visceral fat – this is the fat that is stored both within the abdomen cavity and in the organs. Abdominal fat is already deemed dangerous owing to its ability to actively secrete substances and hormones that can upset metabolic pathways and entrench insulin resistance and diabetes. It has been observed that various measures of central obesity including neck circumference may predict upper-body subcutaneous fat deposition, which is currently recognized as metabolically active and directly linked with metabolic syndrome and diabetes.

**Insulin Resistance and the Implication of Neck adiposity**

The correlation between neck perimeter and resistance to insulin strengthens the case for the use of neck measurements as a diabetes indicator even more. Another pathological process present in type 2 diabetes is the insulin resistance: the body cells’ inability to respond properly to insulin that leads to high levels of blood glucose. A few papers have investigated the relationship between the accumulation of neck fat and the development of insulin resistance and inflammation and oxidative stress, indicating that fat stored in the neck might be metabolically active [13].

Like other types of obesity, neck fat may also release hormones and cytokines known as adipocytes that are involved in controlling blood sugar levels and the ability of cells to respond to insulin. Development of excess fat in the neck area may cause release of pro-inflammatory cytokines and other metabolic active adipocytes that aggravate insulin resistance. Also, higher neck circumference was associated with higher levels of circulating free fatty acids that may interfere with insulin signaling pathways to increase the state of insulin resistance. For this reason, neck circumference might give not only an idea of the total amount of upper body fat but also offer some information concerning the metabolic activity of adipose tissue in neck and, therefore, might be viewed as the predictor of type 2 diabetes risk.

**Neck Circumference as a Diagnostic Tool: It could be viewed as supplementary to other methodologies**

The use of neck circumference in diabetes risk assessment is a number of advantages over the conventional approaches. Although BMI or even waist circumference is an acceptable approximation of regional adiposity, neck circumference may be a more effective measurement of the accumulation of fat in the upper body and its potential effects on metabolism. It is an easily practicable intervention regardless of clinical or non-clinical environment and does not require any additional equipment.

Research has also demonstrated that neck circumference correlates with diabetes when the former is employed alongside several other indices of anthropometry. For instance, incorporating neck circumference in with waist circumference or the waist-to-height ratio could enhance the degree of precision of risk determinations for diabetes as well as other metabolic disorders [14]. This is mainly because neck circumference reflects adiposity in parts of the body not adequately considered by abdominal measurements for this purpose, providing a greater overview of fat patterning and metabolic risk in the person in question.

Further, neck’s circumference useful in prediction of risk, may also help to identify patients those are at higher risk for complications related to DM, particularly OSA. Osa involves repeated episodes of airway obstruction for variable periods during sleep in patients with T2DM and results in poor quality sleep. A previous study has indicated that patients with a larger neck circumference have a high likelihood or OSA since fat in the neck may put pressure on the airway. Thus, besides being used to determine risk of diabetes, measuring neck circumference can also be used to evaluate the presence of other diseases associated with the condition.

**Limitation and suggestions for future research**

However, there is relevant evidence concerning the application of NeC in Sample although there are several disadvantages at its application. The majority of prior investigations has been based on the measurement of neck girth using a flexible ruler to quantify fat accumulation, although this approach could somewhat inadequately represent the composition and distribution of neck fat, as well as its connection with metabolic dysfunction. Furthermore, neck circumference as a risk marker of diabetes may have different thresholds by the age, gender, ethnicity and body composition; thus making a simple cross-sectional study to develop cutoffs for neck circumference unadvisable.

Although neck circumference measurements may yield much information, little is known about the use of neck images as a direct diagnostic aid for diabetes diagnosis [15]. Almost all the current techniques only involve quantification of physical characteristics of the neck and not the features themselves. Though, new technologies in computer vision and machine learning provide a different angle to evaluate neck images as a diagnostic marker. By applying imaging modalities for assessment of skin surface roughness, thickness of the subcutaneous fat, and other morphological parameters it may be possible to obtain a more objective and accurate assessment of diabetes risks than if just relying on the current standard of circumferences.

**Neck Image Analysis: A New Method in Identification of Diabetes**

Neck images for diabetes have a possibility for carrying out machine learning algorithms to discern visual characteristics related to diabetes indicators. Raw images taken with, for example, smartphone cameras can then be fed to algorithms that pick up variations in fat pattern and organization, skin contour, or any other metabolic features that may be visible from the images. This could prove useful since besides the circumference, it would allow for a wider range of data points, which could be used in advanced machine learning to correctly predict the outcome.

In the current study, two main research gaps were found and the current study seeks to fill them by investigating the possibility of using neck images for diabetes detection by developing a viable classification model that can identify individuals with diabetes using neck appearance. This could lead to a new efficient, non-invasive, cheap method of diagnosing diabetes and in turn redesign the management of the disease [16]. The use of artificial neural networks and image analysis in realization of the diagnostic process could also enable the realization of the screening from a distance, particularly in areas where access to health centers is severely restricted.

Neck circumference has proven useful for diagnosis of diabetes and related metabolic disorders because of the link between central obesity and insulin sensitivity. Taking the measurements of neck images as a novel concept to search for diabetes directly has been a relatively innovative approach in research, with the advantage of increasing the chances of early diagnosis and treatment. This approach needs further research as it may be a useful addition to the currently used diagnostic methods, a possible non-invasive screening method and improve the access to the diabetes screening devices [17]. Following the previous research, this study seeks to add on the current knowledge on the unconventional diagnosis for diabetes with the hope of enhancing the delivery of health care services to patients with diabetes in this world.

**Computer Vision for Medical Diagnosis**

Computer vision used in medical diagnosis has been of great credit to society as it makes diagnosis quicker, more accurate and more automated. Computer image based applications have evolved from mere uses in medical imaging modalities like MRI, CT scans and x-ray and currently encompass new techniques of diagnosing various diseases such as skin, eye and cardiovascular diseases. These techniques harness complex models most notably the convolutional neuronal networks (CNNs) to look for outliers or trends within images that are hard to find by normal naked eye scrutiny. Consequently, the application of computer vision has become valuable for enhancing the early diagnosis, the accuracy of the diagnosis as well as the overall patient experience in the medical world.

**Convolutional Neural Network (CNNs) in diagnosis of Diseases through medical Images**

CNNs are now considered essential in many computer vision tasks because of their inherent capability to learn features from images in tiers [18]. In medical imaging applications, CNNs are capable of handling large amounts of visual information that are needed to perform image segmentation, object detection, and classification remarkably well. Its common structure composed of several layers as a convolutional layer, a pooling layer, and a fully connected layer, is effective at extracting raw feature data of images. The convolutional layers detect the specific features that may be present in the image, such as edges, textures, shapes etc., Almost like how we can see an object or image and recognize specific features, such as texture etc The pooling layers on the other hand shrink the dimensionality of the data while only preserving the maximum or average values from the previous layer. Connected layers then make predictions out of the extracted from the previous layers features.

In regard to healthcare application, CNNs have been used to classify images of different types. For instance in radiology, CNN based models have been shown to perform better in nodule detection from the chest X-rays, brain tumors from MRI images and breast cancer from mammograms. Same in dermatology, CNNs have been used in classification of skin lesions, this distinguishing between malignant and benign skin lesions with the same efficiency as the expert dermatologists. The fact that CNNs can be trained on large databases and then perform well on new data to some extent, makes the networks a valuable asset in creating diagnostic tools that would complement the clinical decision making process [19].

Need for Clinical Settings: Conventional diagnostic procedures normally demand clients to go through healthcare centers for the tests. This can be problematic for the patient with limited mobility, HIV affected patients in the rural setting, or those who cannot afford to pay hefty prices to access health care facilities. Also, the necessary of fasting or taking glucose solution during OGTT may interfere with daily activities due to the unsuitability of the test.

**The rise of the non-invasive diagnostic methods**

However, many of the diagnostic approaches of diabetes that employed blood tests have some drawbacks thus researchers have been looking for other less invasive ways of testing for diabetes. Such innovations are used to eliminate sample requirements for blood, lessen discomfort, and make testing frequent, easily available, and quite convenient. Some of the emerging non-invasive diagnostic approaches include:

1. Saliva Testing

It is now well established that saliva holds a variety of biomarkers that are important to understand metabolic profiles including glucose. Previous studies have investigated the option of monitoring salivary glucose and its relation to blood glucose level and the results were encouraging. Despite the fact that saliva testing is still in the experimental stage, people have shown relatively high interest in easy, painless and fast diabetes screening. It is most likely that new gadgets that can detect glucose levels in saliva with great precision could offer a great help to such people.

Healthcare is an emerging field where yolo models have produced excellent performance in the identification of skin lesion and chest X-ray abnormalities. They provide speed and ease which is convenient when used in the screening of treatment of skin cancer and increasing the organizational effectiveness of clinical practice in radiology.

**YOLOv8 Implementation on Diabetic Detection through Neck Image**

In this work, the neck image-based diabetes detection using YOLOv8 demonstrated a new approach in non-traditional medical imaging using computer vision. Images of the neck do not have to be taken using complex machines as other medical imaging options and this means that neck images can be taken using simple cameras such as the ones found in smart phones. For this purpose, YOLOv8 is used based on its object detection background augmented by training on neck images to recognize features that can be associated with diabetes-induced metabolic shifts.

As for diabetes detection, fine-tuning of the YOLOv8 model is possible regarding fat distribution, skin texture and other morphological features with higher risk indicators. For instance, a graceful collar size or some skin seam could indicate a tendency to insulin resistance, which is connected with diabetes of the second type. YOLOv8 model requires a dataset of neck images and the corresponding labeling is done based on medical diagnosis of diabetes. These are typically data pre-processing steps like as resizing the images, scaling down the pixel intensities as well as applying data augmentation to add immune factors in the model against over-fitting.

Researchers using the YOLOv8 model can easily employ the model’s fast processing speed and efficient neck image detection for real-time analysis. Early screening of diabetes could also be made possible with the help of this approach especially in a scenario where equipment used in the normal screening process are not easily available. Their applicability to mobile health applications also broadens the ability of such technology to diagnose and screen for diabetes among people who may have minimal physical access to health care services.

**Pros and Cons of CV in Medical Diagnosis**

The application of computer vision in medical diagnosis has some benefits such as automation, standardization and applicability. Analysis of medical images through the help of automated manner decrease the workload of the healthcare professionals to give priority targets that needs a detailed analysis. Moreover, as part of an artificial intelligence system, computer vision models offer dependable and non-subjective results to cut on the variability of diagnostic precision often occasioned by human interoperation. The flexibility of computer vision systems also enable it for application in screening programs where many images needs to be analyzed in the shortest time possible.

Thus, there are still some issues in applications of the computer vision techniques for medical diagnose. The need for high quality labeled datasets for training from the machine learning models present a major challenge. While annotating data, especially in the medical domain, annotators usually lack sufficient expertise, so the labeling process can be challenging and lengthy. In addition, model performance could also be influenced by differences with quality of images, patient characteristics or imaging environment. These factors call for effective preprocessing and data augmentation techniques so as to realize model more generalizable.

A major concern is in the structuring and interactivities of the resultant models, especially the deep learning frameworks inclusive of CNNs and YOLO. While these methods are accurate and can be used in certain applications, knowledge of the way they make predictions is not always clear. One of the main issues that may slow down the clinical adaption of these models is the fact that the models’ recommendations are not fully transparent. There is current activity investigating the use of post hoc methods that will make AI acceptable to clinicians by explaining how the models arrived at their decision.

The use of computer vision techniques such as CNNs and YOLO models in diagnosis presents tremendous possibilities of efficient diagnoses of conditions through early detection diagnosis. YOVLv8 for Diabetes through neck images signifies a new way forward in the application of computer vision to detect the disease, avoiding demerits that are linked to conventional diagnosis. Thus, further development of the various models in computer vision will render the current and future diagnostic tools as more role-playing options that can benefit those in need of non-invasive, possibly accessible and cost-effective solutions to their healthcare issues.

One day in each week is dedicated to data augmentation methods and model optimization throughout the week.

Data augmentation is well-known method in machine learning and computer vision, especially in the image classification. It involves creating artificial data from the existing images by enhancing variations in terms of quantity and quality. This causes the model to perform better than other cases where the model tends to overfit within the data set, this also ensures that the model is capable of giving out proper results on future unseen data. In practice, the size of training datasets can be quite small because it is difficult to obtain labeled examples, especially in applied problems such as medical imaging. The above limitation is solved by data augmentation since it creates new version of the input images thus exposing the model to a greater number of instances.

**Techniques of Data Augmentation in Image Classification**

The first common approach includes basic geometric transformations like rotate, scale, mirror, crop, translate and more, while the second approach includes color space changes like, brightness change, contrast enhancement, saturation change and more. These methods further present variations of the original images in some way so as to affect the orientation, scale or lighting of the model, so as to help the program learn these variations.

Rotation: Moving an object from different angles such as 15◦, 30◦ or even 90◦ helps the model to learn to identify an object or even a feature in the image. For example when identifying diabetic persons from neck images, a slight rotation of the images is useful in determining patterns despite the orientation in which they were taken.

Scaling: Scaling therefore entails enlarging or reducing the sizes of the images. This increases the models ability to recognize features at different scales to variability in image size space. Scale is one of the most useful transformations in medical imaging since the size of distinct features of human anatomy can differ considerably from patient to patient.

Flipping: Rotating images either horizontally or vertically helps to augment the data with mirror images of the original images. This technique is particularly helpful with items that can move in all angles; particularly, the angle orientation cannot be predetermined. When it comes to image recognition of the neck for diabetes detection, flipping could try images taken from a different angle so that the model is ignorant of a side it was captured from.

Cropping and Translation: These procedures consist of fixed or cutting out some portion of the objects in the picture or moving the picture to the right or left in general. This make the model able to shift its attention on different parts of the image, and identify parts that are most important and which may be located anywhere in the image.

Color Space Transformations: Adding and subtracting brightness, contrast, saturation, and hue of images can enable the model to resize images in the face of different lighting conditions. This is especially relevant when testing data sets for which some images were captured in one lighting conditions, e.g., indoor lighting, while others were captured in other conditions, e.g., outdoor lighting.

**How Data Augmentation Helps Models and Their Generalization**

Augmentation of the data is important in promoting the model’s capacity to perform well in other unseen data referring to as generalization capacity. When the model is trained on data based on the augmentation of images by mimicking real world variations, then the model adapted becomes less sensitive with the features contained within the original dataset. This decreases the chance of over fitting where the model performs very well in the training phase but performs poorly in the testing phase. Over fitting is true in this model leading to high performance in the training set but low performance in the test set, which remains a challenge in machine learning especially where we have small data set.

For instance, getting images of the neck for diabetes detection, it means that the use of a small training set of labeled neck images would make the model overstrain on specific features of the training samples. By performing data augmentation techniques the size of the dataset grows and the model can learn from a much larger variety of images. This process helps to boost the probabilities that the subsequent recognition of specified features of diabetes in new pictures will accurately reflect the changes in light or position or whatever circumstances of the new picture taken.

**Hyper parameter Optimization for Model Optimization**

Apart from data augmentation, the improvement in the efficiency of machine learning models also consists of tuning the shame’s hyper parameters. Hyper parameters are the measurements on the outside of the model for which a decision is made away from the learning platform, including, but not limited to, the learning rate, the size of the batch, the epochs, the choice of optimizer, and the value of dropout. All these parameters have direct influences to the training profiles of the model and the overall accuracy of the model.

Learning Rate: The learning rate is as far as how big a step the model’s weights get when training is concerned and it’s a crucial factor to consider when fine tuning a neural network. While completing the training in fewer iterations with a faster learning rate it could compromise and settle on a low accuracy solution. On the other hand a small learning rate ensures slow convergence to the correct result but provide the model the best possible state it can achieve. I suppose that one of the most important aspects of any deep learning algorithm is calculations of learning rates because gradient descent algorithms to minimize a loss function are dependent on learning rates.

Batch Size: The terms ‘batch size’ refer to the number of samples that go through in one cycle in a machine learning cycle. The former has the added benefit of being able to take more advantage of the computational capabilities of GPUs, but the latter is the problem that large batch sizes are less frequently updated which hinders the convergence. This is because one goal of adopting a small batch size is to get more frequent updates for the model, which provided us with an accurate optimization of the model on the other end it takes a long time during training. The next technical decision is selecting an appropriate batch size and this is a critical step because it determines the ratio of learning rate to speed.

Number of Epochs: The number of epochs: An epoch means you have gone through the whole set of different samples of the learning data once. The training is conducted epoch wise for the best results; however, many epochs could lead to over training.

Optimizer Selection: Various types of optimizer for example stochastic gradient descent (SGD), Adam, RMSprop, AdaGrad etc come with their characters that help to train the model. Nevertheless, simple and heuristic like SGD is good for a variety of tasks, complex methods such as adaptive methods including Adam which utilizes the first and second moment for estimating learning rates are preferred in deep learning models. Hence the selection of optimizer plays an important role in the speed with which the model converges as well as its overall accuracy.

Dropout Rate: Dropout is another kind of regularization methods in which a particular randomized proportion of neurons output is cropped out during the training phase. The dropout rate defines the number of neurons which should be dropped. This rate can then be tweaked, in order to move the trade-off, between regularization and model capacity, up or down, as needed.

**Effects of Hyper parameter tuning on Generalization of Models**

Optimization of hyper parameters is very crucial for better expectation and performance out of the model. It is a fact that an increase or decrease in a small value of hyper parameters leads to large variations in the performance of a model. For instance, choosing an appropriate learning rate can mean that the model will have a fast convergence and will not end up at a local optimum. The same way, changes in the batch size may have an impact on the gradient estimating step and impact is the ability of the model to generalize to other data sets.

Here, fine-tuning of hyper parameters is quite important while dealing with neck image classification so as to analyze the results on a real-time data set for diagnosing diabetes. Thus, with help of several hyper parameters like learning rate, batch size and number of epochs, the model can be trained to fit the training set well while still having relatively good cross validation result. Furthermore there are ways to train the model that were over fitting such as the early stopping where training is stopped after a specified number of epochs without improvement in the validation loss.

In essence, data augmentation and hyper parameter tuning are basic processes which are applicable for boosting the performance of image classification models in the machine learning. In the case of detection of diabetes using neck images these techniques help ensure the model’s ability to detect patterns, although the neck images may look quite differently, to contribute to the creation of a non-invasive diagnostic tool in the near future.

**Possibilities and Problems of Using Machine Learning in Medical Diagnosis**

The use of ML in medical diagnosis has received much attention because of the possibility to reshape the healthcare system. These higher-powered algorithms are able to process large volumes of data in order to conclude on trends that would otherwise be undetectable using conventional diagnostic techniques which will therefore assist healthcare practitioners in arriving at better decisions. But learning with machine has its demerits especially when it comes to diagnosing the health of the patients. Such problems as data quality that affects the accuracy of models, interpretability of models, and proper handling of ethical questions remain important when it is time to implement such technologies in clinical facilities.

**Data Quality and Representation**

The most important problem which arises when applying machine learning to medical diagnostics, is the quality of the data which are used to train models. In order to train an effective and efficient machine learning algorithm, high quality of data is vital. There are several problems associated with medical datasets, including the presence of records with missing data and inconsistency of the data tested between several sources. These data quality issues can result in developing biases models which in some cases generate wrong predictions. Therefore, it can give high percentages of false negatives, meaning no signs of an illness is predicted by the model while some patients are ill.

In addition, it is critical that its training set up represents sample of the data most closely possible. Medical datasets need to be generalized and should contain people with different ages, gender, and ethnicity and with or without other illnesses. The lack of diversity results in modelling that endangers those that are not originally included in the model, thus continuation of the health differences. For instance, when a model has been trained on a specific group of people, the equity in model-powered healthcare decisions will be impacted; making it poor in handling a different group of people’s healthcare. Hence, it is critical that the model that is developed is trained on diverse and yes) datasets to avoid model bias and perform well on different targets, customers and clients.

**Model Interpretability**

The last pivotal challenge to healthcare diagnosis with the use of machine learning is the aspect of explaining the results. Although techniques like deep learning models can provide a very high degree of accuracy, they say little more than “it’s a black box.” This means that, the decision making processes of these models are relatively complex and therefore may not be comprehensible even to the modelers who developed them. In the general arena of health care, that involves decisions that may have broad consequences for the course of an individual’s health, opacity of the decision process can be undesirable.

In general, decision makers in healthcare need to know how a model got there to trust the model’s recommendation. For instance, a doctor using the model may want to know why such a diagnosis or treatment was ticked without using a model to guide him. It is for these reasons that the concept of explainable artificial intelligence (XAI), is a rapidly emerging trend in medicine. Both academics and professionals are currently doing extensive research on how to better explain the rationale as to how the feature of the data affects the resulting machine learning model.

Greater refinement of the interpretability of models can result in the higher effectiveness of teamwork and integrated cooperation with HL. Clinicians can confirm how accurate the model’s suggestions are as well as recognizing any likely mistakes to give optimum patient care. For instance, if a model gives high risk of diabetes from neck images, the clinicians must know which factors in the images led to the result. Such transparency can help in decision making by practitioners, patients, and insurance companies and hence help accept machine learning tool in clinical practice.

**Ethical Considerations**

There is a myriad of ethical issues that have to be discussed or considered each time when machine learning is used in making initial diagnostic decisions. One of the key issues is, therefore, algorithmic prejudice which arises where the data employed to train an algorithm mirrors prejudice in the healthcare system. For instance, if certain populations have either been less represented, or have been historically provided less adequate care, then machine learning models learned from such data will also preserve such social injustices.

Also, patients’ records’ confidentiality is highly relevant since patient data is highly sensitive. Healthcare data often have information belonging to the patient that needs to be well protected to enhance the patient’s privacy. Technical steps involve implementing machine learning algorithms based on solid data management and safety policies to meet legal requirement in the United States by HIPAA and in Europe GDPR. To maintain patient’s privacy, researchers and other care organizations must develop ways of blurring the models’ training data to prevent other people from accessing it.

Moreover, relying on the machine learning for diagnosis also has its significance issues other than mere technicalities. Such concerns are whether or not the AI systems should be held liable for their mistakes. When a model is used to diagnose patient symptoms, or recommend the appropriate course of action, it becomes hard to ascertain who is to blame when they get it wrong. AI systems which take decisions must have body policies and procedures to address questions of responsibility when things go wrong.

Completeness and unbiased presentation of data are the factors that define the reliability and unprejudiced assessments. Also, improving the model interpretability about the results, using explainable AI methods is vital to gaining the trust of healthcare workers. Last but not least, concerns that relate to bias, privacy, and responsibility maintenance must remain topical as applied to the performance of healthcare systems with a focus on the ML algorithms utilization. With these, healthcare community can take good advantage of machine learning for enhancing patient care and the prospects of diagnostic in forthcoming years.

## **1.6. Contributions of the Research**

This research also has several important implications to the diagnoses of diabetes, mechanics of medical image analysis and using machine learning in health systems. The key contributions are as follows:

Novel Diagnostic Approach Using Neck Images: The presented work presents an original approach to diabetes detection through analyzing of the neck images, which is a breakthrough compared to the methods used up to date such as blood tests. Through embracing computer vision methods, the study aims at finding applicability of image analysis based diagnoses that would fit into intensive and accessible diagnostic approaches relative to the conventional practices.

Expanding the Use of Computer Vision in Healthcare: Computer vision has been applied to medical imaging most commonly for purposes such as tumor detection, skin lesion classification etc., whereas the use of neck images for the detection of diabetes has not been tried earlier to the best of our knowledge. This research broadens the application of computer vision in medical diagnosis by proposing techniques for analyzing other factors which are unrelated to disease diagnostics but could be included as diagnostic approaches.

Development of a Machine Learning Pipeline for Image-Based Diabetes Detection: The work describes how an ML system with data acquisition at the input end, and result analysis at the output end, was built. By applying the YOLOv8 model, which was trained on extensive benchmarks in object detection tasks, one can observe the possibility of approaching with state-of-art computer vision methodologies to solve healthcare issues.

Practical Insights into Data Augmentation and Hyper parameter Optimization: Conducting comprehensive data augmentation trial and hyper parameter optimization, the paper outlines the solutions that enable improving model efficiency in the medical image classification task. These findings are relevant not only for this particular research but also for further studies applying machine learning methods to other tasks within medical image analysis.

Contributing to the Understanding of Neck Circumference as a Diabetes Indicator: The study also contributes to the relatively emerging literature that illustrates that neck circumference and other apparent cues are potential markers to metabolic diseases such as diabetes. Through exploring the pattern of neck image characteristics and diabetes diagnoses, the study might open up the possibility of subsequent explorations into other diseases’ markers based on body part characteristics.

Potential for Real-World Application in Mobile Health (mHealth) Solutions: This paper aims at establishing the possibility of integrating diabetes detection models in mHealth applications. Thus, setting out the prospect of creating mHealth solutions based on the use of a smartphone camera to diagnose diseases, the study provides consistent prospective to the development of applications that will function in the regions where the conventional forms of healthcare resources are scarce.

Ethical Considerations and Model Transparency in Medical AI: The study fills a gap in the discussion of some of the issues that pertain to the moral utilization of AI in the health sector; the issue of model interpretability, explain ability and the issue of using AI to diagnose diseases. The findings add to the current discussions on the thematic of the practicing AI’s responsible usage in healthcare.

## **1.7. Structure of the Report**

This report is organized into several chapters, each addressing a specific aspect of the research:

* Chapter 1: Background to the Study – Presents a background to the area of research by defining the problem area, research objectives, area of study, and need for the research. It also describes the major findings of the study and a brief overview of the report.
* Chapter 2: Literature Review – Considers possible sources of information concerning diabetes detection, various non-traditional corners of diagnostic tools, and a connection between computer vision and machine learning to medical diagnostics. In this chapter, literature on the ability of neck circumference as a predictor of diabetes is discussed and research limitations that this study seeks to fill are presented.
* Chapter 3: Methodology – This work describes why YOLOv8 model is used and which preprocessing and data augmentation were chosen for the task.
* Chapter 4: Data Analysis and Results – Outlines the outcome of the; Model Training and Model Evaluation stages. To this chapter are provided performance indicators as are accuracy, precision, recall, F1-score, and considerations as to the factors that affect model performances.
* Chapter 5: Discussion – Explores further the outcomes with regard to the identification of diabetes and the possibility for noninvasive diagnostic strategies. It also discusses the constraints of research and proposes recommendations for the subsequent research.
* Chapter 6: Please find below the Conclusion and Recommendations – Main findings of the research are presented, its significance for the field is discussed, and recommendations for practical usage and further research are given.

Appendices – including all about the model configurations, extra outputs from computational and data analysis, and illustrations of code snippets of the machine learning pipeline.he research topic, outlining the problem statement, objectives, scope, and significance of the study. It also presents the key contributions of the research and a summary of the report's structure.

* Chapter 2: Literature Review – Discusses existing research related to diabetes detection, unconventional diagnostic indicators, and the application of computer vision and machine learning in medical diagnosis. This chapter reviews the potential of neck circumference as an indicator for diabetes and highlights gaps in the literature that this research aims to address.
* Chapter 3: Methodology – Describes the research methodology in detail, including data collection, image preprocessing, machine learning model development, evaluation techniques, and validation processes. It explains the choice of the YOLOv8 model and the rationale behind the selected preprocessing and augmentation techniques.
* Chapter 4: Data Analysis and Results – Presents the findings from the model training and evaluation phases. The chapter includes performance metrics such as accuracy, precision, recall, and F1-score, as well as discussions on the factors influencing model performance.
* Chapter 5: Discussion – Provides a detailed analysis of the results, discussing their implications for diabetes detection and the potential for non-invasive diagnostic techniques. It also addresses the limitations of the study and suggestions for future research.
* Chapter 6: Conclusion and Recommendations – Summarizes the main findings of the research, discusses its contributions to the field, and provides recommendations for practical implementation and future studies.
* References – Lists all the academic sources, articles, and literature cited throughout the report, following the appropriate referencing style.
* Appendices – such as detailed model configuration settings, additional data analysis, and example code snippets used for the machine learning pipeline.

## **1.8. Background and Significance**

This disease affects millions of populations globally and is linked with the following risks; cardiovascular risks, kidney risks and neuropathy risks. The established techniques for diagnosing diabetes are biochemical and depend on blood tests, including fasting blood glucose level, oral blood glucose tolerance, and HbA1c.

Due to improvements in technologies and trends in medical practice, people are now demanding for early and noninvasive techniques to diagnose diabetes. Thus, one of the growing fields of interest involves the application of physical measurements, including anthropometrics, as possible indicators of diabetes and some other metabolic disorders, including neck circumference. A relationship between upper body obesity, specifically neck circumference and insulin resistance both of which are germane to type 2 diabetes, has also been established. Some papers have found a direct relationship between living diabetes and increased neck size irrespective of BMI figures.

At the same time, the field of artificial intelligence including machine learning has been keenly developing especially using computer vision in medical imaging. Retail applications of ML have involved the identification of objects in retinal, mammography and chest x-ray images for the general diagnostic and screening processes. However, there are a lot of unknown issues on using AI in detecting diabetes based on neck images. This fact creates a research gap, which may support the question of whether or not it is possible to apply computer vision to analyze properties of the neck for diabetes prediction.

This study can be beneficial as a noninvasive, cheap, and readily available diagnostic method, which can be used as an addition to the current diabetes screening instruments. With smartphone cameras, the approach may help to screen diabetes with neck images in remote regions where patients may not be able to visit clinics, or hospitals repeatedly, and help the needy patients to get diagnosed in the preliminary stages. In addition, it complements the growing interest in individualized and mobile approaches enabled by advanced technologies for supporting people in chronicle diseases.

Taking into consideration the constant increase in the number of diabetes cases and the continuous necessity for the creation of the new diagnostic methods, this research tries to contribute to the improvement of computer vision in healthcare and the investigation of the unconventional biomarkers for the diagnosis of diabetes.

# **2.0. Methodology**

In the current study, various processes are described regarding the overall approach used for the identification of diabetes through neck images. Since neck circumference has been recently recognized as a possible risk factor for Emergence of diabetes this study aimed at building a feasible noninvasive diagnostic solution utilizing advanced image analysis. The major steps used throughout the presented work and in general, include data acquisition, image preprocessing, selection of the model and evaluation of its performance, which is vital for the attainment of the set objectives.

## **2.1. Techniques**

In an attempt to enable the identification of the types of images captured on the neck that can inform the identification of individuals with diabetes using neck images,, a rigorous approach was followed from data acquisition to the current analysis. The first procedure included capturing neck images from individuals, using only smartphones. This way, not only was reach ensured but also flexibility and, thus, improved resistance of the collected sample of images. Recruitment criteria for the study involved medical history with regards to diabetes; this means that the researchers were able to tag the images in accordance to the medical disorders confirmed by participants. This led to the formation of a two category data set in an attempt to classify those with diabetes against those without diabetes.

Preprocessing in this case can be said to be extremely crucial. Raw images, for instance, come in different resolutions and lighting environment and this hampers the model performance. As a result, several preprocessing steps were applied here including. First, all images were normalized and scaled to the size of 416×416 pixels. . Further, pixel intensities were normalized in order to standardize this data in preparation of preprocessing data to scale the values this is essential since it enables quicker convergence during training.

However, to improve the usability of the obtained data, data augmentation was applied next step. Such measures as rotation and scaling are central to addressing the problem with a model’s ability to generalize. In a way, these techniques ‘inflate’ the size of the dataset and improves the model’s generalization in areas of unseen data. This is particularly a big issue in diagnostic prediction tasks, given that real-world diagnostic models will be applied to unseen, diverse patient populations. Data augmentation is also useful in avoiding emergence of over fitting since it optimizes the results already obtained.

Another important feature of the method was the selection of the model. The choice of the YOLO model and the YOLOv8 for the current work is based on the high practical performance in the field of object detection and classification at the current stage. These are real-time models, which are very recommended in clinical work processes because timely decision making greatly affects the results. The YOLOv8 model is fast and accurate by design based on its architecture to point it to applied use in the diagnosis of medical images.

For the training procedure Google Colab was used which had computational access of a Tesla T4 GPU. This cloud-based system is best suited in running comparative tests on machine learning for big data preprocessing. Special configurations were applied to the programming environment: Python 3.10.12, the NVIDIA driver 535.104.05, CUDA 12.2. Some of these technical specifications were important for us in order to guarantee that model training was going to be efficient and seamless.

The training process in its turn unfolded the necessary tuning of several conveniently adjustable hyper parameters such as learning rate and batch size as well as the number of epochs. Hyper parameters are unique from parameters as they dictate model learning and thus hyper parameters tuning is important in the model optimization process. Learning rate signifies the rate at which the model is trained and a well-adjusted learning rate = enhances convergence. Batch size a process of using a certain number of training examples every time the model is trained typically influences the stability and the rate of training on the model. Moreover, total epoch means the number of times the learning algorithm goes through the training set. Thus, changing these parameters in some satisfactory way was the main goal of the research team so that model performance was maximal.

When the model was trained, model accuracy, precision, recall, and F1-score were measured. All these measurements give an overall sum up of how good the model has been in identifying diabetes through the images of neck region. Accuracy defined as the ratio of the correctly identified observations in relation to the total number of observations that have been analyzed, while precision defined the ratio of the correct observations out of the total observations that has been predicted as positive. On the other hand, Recall calculates the extent to which all the instances of the model can be retrieved from the dataset. The F1-score can be calculated as the harmonic mean of the precision and recall values, giving you both values at the same time. All of the mentioned kinds of evaluation criteria summarize the model’s benefits and possible drawbacks, which can then be addressed and changed.

In a nutshell, the present methodological chapter outlines a clear procedural framework on how neck images can be employed in diagnosing diabetes. Introducing the methods to data collection, preprocessing, model selection and evaluation, the research is intended to lay the foundation for the further development of this field of investigation of non-invasive diagnostic tools in the healthcare domain. The subsequent sections will further describe the outcome of the implemented method and consider various application of the results in subsequent research and clinical practice.

## **2.2. Tools/Libraries**

When building an effective machine learning model for detecting diabetes using images of neck some tools and libraries were used to enhance collection, pre-processing, training and assessment of the model. The decision to use these tools proved significant in harvesting the research objectives in a no dubious and expeditious way. The following section outlines the complete list of tools and libraries which were employed in the whole process of the research.

1. Data Collection Tools

During the initial data collection process, photos of participants’ necks were taken only with the cameras of their smartphones. The reasoning behind selecting this tool rooted from the recent advancement in the Smartphone’s camera that has turned more into powerful image acquisition instruments. Smartphones allowed the researchers to take lots of data without having to invest in expensive hardware, which improved the study’s accessibility. In the data collection process it was made sure that all the images were taken under the same level of lighting and from the same angles which are very important when collating such a data set.

2. Image Annotation Tools

After gathering the neck images, the proper labeling of images needed to be conducted according to the diagnose of diabetes. To this end, there are applications including Labeling or VGG Image Annotator (VIA). These tools enabled the researchers to put a rectangular frame around the neck regions in the images and also put labels notifying the diabetes status of the respondents. Annotation is crucial for supervised learning problems because a low-quality set of labels determines the model’s training and its practical use in real-world scenarios.

3. Data Preprocessing Libraries

Data preprocessing is one of the most important aspects of the image preparation processes for the machine learning model. Several Python libraries were used to facilitate this process:

* OpenCV: This open source, high powered computer vision library was used in image manipulation operations involving resizing the images to this required resolution of 416 x 416 pixels. In the same manner, using OpenCV is important in handling algorithms since its operations involve many functions of image processing.
* PIL (Python Imaging Library): This library was also employed in some simple image pre-processing exercises such as standardization of pixel intensity values. Normalization support the standardization of the input data where most neural networks models converge faster during training by making most pixel values fall within a similar range.
* NumPy: NumPy is one of the basic packages needed for numerical computations in Python; it was used intensively for reorganizing image arrays and making mathematical manipulations on pixel values.

4. Data Augmentation Libraries

Data augmentation was also used to make the model generalize from the training data that was used in this study. This in essence enlarges the training dataset by applying different transformations to the images artificially. The following libraries were instrumental in this regard:

* Augmentations: This widely used library of image augmentation was used to add various transformations such as rotation, scaling, flipping, etc. Augmentations is considered one of the fastest transformation functions for the augmentation of models, while providing the ability to tweak strategies used in model customization.
* Keras ImageDataGenerator: This built-in Keras’ class was also discussed while real-time data options for augmenting data happening during the training process, would also generate batch of the augmented image data.

5. Machine Learning Frameworks

For the implementation of the YOLOv8 model, the following libraries were utilized:

* PyTorch: YOLOv8 model is developed in PyT Torch, an open source machine learning library that offers reversible representation for the building of worlds’ simplest and most dynamic neural networks. PyTorch was selected due to simplicity and a large population of users, which means that the research team can take existing utilities while customizing some to the project’s needs.
* Ultralytics YOLOv8: In this study, the YOLOv8 version created by Ultralytics was used for object detection and classification purposes. The user interface of this library for training and deployment of YOLO modes makes it suitable for this research. It has built-in models and assessments that help the user to incorporate them into his/her practice more smoothly.

6. Development Environment

Google Colab is an interesting tool that enables users to write and run Python code in a Jupyter notebook which is most appropriate when it comes to data analysis and Artificial intelligence. The availability of GPUs for training deep learning, the platform can potentially train several models at once which shorten the training time.

* Google Colab Features: Google Colab was used to train the model having a Tesla T4 GPU make the computation much faster than before. A software environment was defined with Python 3.10.12, NVIDIA driver version 535.104.05, and CUDA version 12.2 as these are standard requirements to maintain compatibility with the training process.

7. Performance Evaluation Tools

#### Once training of the model was complete, it was important to perform benchmarking of the same to ensure that it satisfied the research objectives. Open source libraries such as Scikit-learn were used to evaluate the model’s accuracy, precision, recall and F1-score. Scikit-learn is a powerful tool of portable and high quality tools for data mine and provides important indications for the evaluation and selection of the model.

#### Therefore, the tools and libraries used in this research proved to be crucial in the correct application of the proposed methodology for detecting diabetes through neck images. Each one of them was designed to perform several tasks in the work with the data and the models of the diagnostic framework, including the data gathering and preprocessing and the training and evaluation of the models. The use of modern technologies and effective methodologies indicates the possibility of applying progressive practices in the diagnosis of diseases especially noninvasive approaches.

## **2.3. Software Solution**

#### The software solution created for diabetes detection by processing neck images has different components that are implemented to provide an effective workflow from image acquisition and data processing to applying the created models. This solution is not only based on my deep machine learning algorithms however, it also uses great programming environments and frameworks to easily confine along with improving the diagnostic process’s efficiency.

#### Data Collection

#### Participants’ neck images were obtained with their permission, using the camera of their mobile phone, to get high-quality pictures and avoid light variation. The images were coded to come up with a classification data set with two classes namely diabetes and Non-Diabetes. Prompts were kept ethical, having informed-consent and the privacy of medical information in order to acquire patterns correlated with each of the categories.

#### Data Preprocessing

After data was collected, several preprocessing procedures were utilized in order to get the images ready for model training. All the images were rescaled to 416 X 416 pixels because most of the CNN models require a similar dimension to the input image to enable uniformity of the relevant set.

Information normalization was also done on the pixel intensity to increase pixel intensity values to 1. This step is important as it helps to make sure that during training, the model converges well and there is not extreme features dominating the other features because the ranges are very large.

Further, to increase the size of the dataset and its diversity standard form techniques such as resizing and normalization were performed Data augmentation was also used to expand the dataset artificially. Some of the worked done on the images include rotation, scaling and sometimes flipping. This augmentation process is crucial to enhancing the generality of the model, as it offers the model a wider chance of confrontation real-life-case use. Just as some officers are added into the training set, the model learns more widely and it does not easily become over specialized to the training images used.

**Model Selection and Training**

As for the basic module of the software solution, the YOLOv8 model of the Ultralytics Company was selected, as it showed high efficiency in object detection and classification. The second model is YOLO, an acronym for You Only Look Once; it is among the most accurate and fast models that are ideal for instant diagnosis in the moments that the disease has advanced and has a dangerous effect on the human body. This is important for the differentiation of images, necessity to recognize both objects and classify neck images as diabetic or non-diabetic.

The training of the model was done using Google Colab, an environment that allows the use of GPUs which are expensive to acquire. In more detail, a Tesla T4 GPU was used to improve the computational speed of the training phase. Environment for development was chosen and prepared to work on multiple languages, its configurations included – Python 3.10.12, NVIDIA diverters. 535.104.05 and CUDA 12.2. These specifications are important to run deep learning models efficiently in Parallel through massive computation power that GPU provides.

In the training phase, many hyper parameters were tuned to get the best result on the model. These parameters included the learning rate which determines how much to change the model based on the estimated error for each update of the weights; batch size, which defines the number of samples that are taken in one round through the entire training set; and number of epochs, which defines the number of complete passes through the entire training set that the learning algorithm is to make. Some of these require tuning due to the fact that they can define the performance and the ability of the models for generalization particularly in areas of complexity distinctly.

**Model Evaluation**

After training, all the performances of the YOLOv8 model’s accuracy, precision, recall, and F1-score were tested and comprehensively assessed. Accuracy gives an overall measure of the correctness of the model while Precision and Recall gives detail of the model with referring to the positive class (diabetic). The F1-score acts as the median of the two metrics we have looked at because it takes into account both the precision and recall This makes the F1 score particularly useful in situations where there is likely to be class imbalance. Hence the evaluation of these metrics; a detailed appreciation about the performance of the model will be made, including recommendations that will enhance the productiveness factor of the model.

* Altogether, the proposed diabetes detection software is a complex integration of data acquisition and neck image preprocessing, machine learning model training, and assessment. All of them have been designed and installed to guarantee reliable and effective diagnostic tool; it indicates that more possibilities of creative methods on non-invasive diabetes diagnosis can be developed.

There are two types of requirements namely, functional and non-functional requirements.

* In the process of developing the software solution which will detect diabetes based on the images of a neck, the functional and non-functional requirements have to be taken into account. These requirements are important to guarantee that the system functions according to its intended purpose while satisfying the needs of its users as well as providing two high functionality and usability.

**Functional Requirements**

From the functional requirements it is possible to identify all specific activities that are to be supported by the system for the users. In the context of this project, the following functional requirements were identified:

User Authentication: It should be possible for different users, including the healthcare workers and researchers, to sign up into the system and then login to the accounts. User authentication modifies that only certified individuals and personnel entitle to see controller medical information get access to it.

Image Uploading: Neck images should also be uploaded conveniently through the system interface for its usefulness to the users. It should be able to accommodate different aspects of images, including JPEG, PNG, etc; and guarantee that images are properly captured and processed.

Image Labeling: The system should include features of annotations for images that is uploaded based on diabetes diagnoses. Users should be allowed to tag the screen I, II or III depending on the presence of diabetes in the individual.

Data Preprocessing: Functionalities for automated preprocessing of images are also necessary for the software, including image resizing, normalization of pixel intensity levels and data augmentation. All these procedures should be done consecutively in order to prepare images for model training.

Model Training: Users should fine tune the hyper parameters and decide on the required training parameters.

Model Evaluation: Once the training is complete, the software must apply the above factors to determine the correctness or otherwise of the given model through general parameters such as accuracy, precision, and recall as well as F1-score. The results should be given in a format that you can easily likely visualize using graphs/tables etc.

Reporting: The system should be capable of issuing report that captures all the analysis made by the model and diagnostic predictions available. The figures provided above remain useful in decision making within healthcare practitioners after extremes have been conduct.

Data Management: It should allow easy access to the data, for viewing, changing and even deleting both the images and the labels associated with them.

**Non-Functional Requirements**

This covers the aspects of the Quality of service and it can be Physical or: Nonphysical Non-functional requirements = quality attributes of the system. The above requirements are important in making the system accurate, time efficient or even user friendly. The following non-functional requirements were identified for the software solution:

Performance: The system should be able to download and process images and train this model with less time taken. Minimal time for the response of images up, and preprocessing of images should be expected, and the training of the model should make effective use of computational resources.

Scalability: The software should accommodate a growing amount of data and the user’s requests. The system has to keep up the performance irrespective of the frequency at which participants are uploading their images.

Usability: The application should be as flexible and simplistic as to allow interaction with the system by different users with unfixed proficiency levels. Usability is an important factor that can also be used to promote content analysis and so improvements should be made on instructions and feedback.

Security: First, since the information processed by the system is medical data, the system needs to have a strict security regime, such as encryption, authentication, and others, which would help the system meet the necessary legal requirements.

**Reliability: The software should have high availability and reliability meaning the ability of the user to access the system and the facilities without intermissions.**

**Compatibility: The software solution also needs to be quite portable so that users can easily use it on desktops, laptops, tablets and phones with little problem.**

**Maintainability: The set of code of the software should be clear and refined, so that there will be less difficulty that the developers will encounter in the future should they need to edit or modify the software system. Ideally, additional improvements and correction of vulnerabilities should be scheduled to occur on a routine basis in order to improve the functions of the software.**

**Therefore, heads’ protrusion and size, that shaped the functional and non-functional requirements for the software solution, play a vital role in achieving the overall objective of the software – diabetes detection through neck images. If all these requirements are met, the development team can be certain that users of the system get value as is intended by improving on non-invasive diabetes diagnostics.**

**Explanation of Personnel and Facilities**

**The diabetes detection project using neck images need a professional team, and enough conditions including data acquisition, data pre-processing, developing models, and testing models to complete it smoothly.**

**Project Manager: The roles of a project manager are to schedule a project, set working standards of time and cost, maintain communications between team members during the development process, oversee stakeholders’ expectations, and address any problems during the development.**

**Data Scientists: The discovery and optimization of the machine learning algorithms used in the project requires experts in the application of data. All the components of the model’s architecture, the features of classifying data, and data preprocessing are created by professionals in statistics, programming, and machine learning, so this model is effective and fast.**

#### **Software Developers: Software developers have the challenge of creating the application framework for uploading, preprocessing images and training the model. These are active in the backend and frontend, and it makes the frontend excellent where the visitors interface with the tool and backend insightful where the essential mechanisms function. An understanding of programming languages including Python, and JavaScript and knowledge on machine learning libraries is essential to their work.**

#### **Data Collection Team: This team is also involved in the collection of the dataset of neck images. They interact with the participants, guide them on how best to take proper pictures using their phones, and observe any research ethical consideration such as getting permission from the participants in order to be able to take photos of them while observing the do-not-photograph rule of not taking photos of participants’ faces. As a matter of facts, their role is basic in so far as it provides the quality and reliability to any given data set.**

#### **Quality Assurance (QA) Testers: QA testers are supposed to be zealous in their effort to check for any defects in the software solution they are working on before deploying the solution. The testing methods used guarantee that all the inherent aspects of the program perform as required and that operation is seamless and user-friendly. Their focus is very important when it comes to sustaining the high-quality and dependable product.**

#### **Medical Advisors: Diabetes detectability is as explained by clinical consultants with medical expertise. They advise the team on which medical metrics are appropriate to use for the model and explain the results in light of medical theory. They guarantee that the project entails standard knowledge of any clinical practice that is required out there.**

**Facilities**

Office Space: Team members working in project teams must have their own offices or area where they could be in touch and deal with matters which arise. There should be several meeting rooms, working places and recreational spots that include area for meetings and discussions. There are benefits for productivity and even for relations between people in a workplace and team when the environment is well arranged.

Computer Lab: The lab should have adequate graphics cards; enough RAM to support computations, more specifically for big data and complicated computations.

Cloud Computing Environment: Due to the computational requirements for model training in a machine learning model, the setup requires access to a cloud computing environment, mostly colab Google or AWS. This facility helps the team to utilize stronger GPUs, the fast model training and the experimentation which is not possible due to constrained local hardware.

Data Storage Solutions: Durable data storage facility is important to preserve safely, the neck images data set as well as, the models and result achieved during the project period. There are options for cloud storage of data that offer the functionality for growth while also maintaining security for the data, so it can be accessed by the team members whenever needed.

Communication Tools: Communication tools should be used in the provision of collaboration especially if some of the team members are remotely located. Messaging apps including Slack or Microsoft teams, or collaborative apps like Zoom keep everyone communicating in real-time as well as sharing files and holding virtual meetings, enabling the team to be productive beyond the confines of a physical workplace.

Briefly summarizing, the personnel that is involved into the project of diabetes detection includes people of different background and expertise but all significant to the success of the project. Combined with proper infrastructure and technological support, it intends to offer a novel and efficient approach to identify diabetes from neck images at a group level.

## **2.4. Hardware Requirements**

#### Using neck images to implement a diabetes detection project entails specific hardware part that allows for the data acquisition, processing and modeling of the project. This part of the project explanation provides information concerning the basic hardware requisites for the proper implementation of the project.

#### 1. Personal Computers and Workstations

#### A set of high performance personal computers – also known as workstations is essential part of the development team. These machines should be equipped with the following specifications:

#### Memory (RAM): 16 GB of RAM should be provided as a minimum for work with big data, as well as for operation in several applications concurrently without a decline in performance. For intense operations like model training 32GB or higher may be considered preferable.

#### Storage: SSDs with a storage capacity of not less than 512 GB in order to enable speed of read and write operations for enhanced access to data and the software applications. Another form could be using additional hard disk storage (HDD, further down labeled as Blob Storage) for archival usage.

#### 2. Graphics Processing Unit or Graphic Card

#### The primary requirement for model training is that deep learning frameworks require a powerful GPU. The following GPU specifications should be considered:

#### GPU Model: High-performance GPU commonly NVIDIA Tesla T4, RTX 3080 and its kind that can perform parallel tasks efficiently. Specifically, the observed effect of the GPU selection on the training speed and the performance of the targeted machine learning model.

#### CUDA Support: The equipment must have CUDA (Compute Unified Device Architecture) compatibility allowing to run DL algorithms tailored to NVIDIA GPUs. Precisely, this capability improves computational effectiveness when implementing the model in a machine.

3. Smartphone Cameras

Because data is being collected by capturing neck images of the participants, quality smartphone camera are required. These cameras should have the following features:

* High Resolution: Portable devices with image capturing capacity of at least 12 MP or better for the clarity of the necklace images. Having high quality image increase input data quality that fed into the machine learning model.
* Stable Capture: The smartphones should have stabilization in them or accessories ( Tripod) so as to reduce blurriness when taking the images, thus improving on the quality of the dataset.

4. Networking Equipment

Dependable networking equipment are crucial in providing easy and efficient means by which people in a particular working team can communicate and share information as well. The following items are essential:

* Routers and Switches: A high speed of routers and switch to enable the members of the team to access the cloud resources and other files at a very high speed.
* Wi-Fi Access Points: Extra connection points may be needed to guarantee coverage of all space in the office, to provide all employees with connection opportunity.

5. Data Storage Solutions

Overall large amount of data is generated at various point of time during the project; thus sound data storage practices are required. These solutions should include:

* External Hard Drives: Exterior hard disk drives for archive of large datasets, checkpoints and creates or modifying projects. The duplication, therefore, enhances data protection while making certain that all essential data is well preserved.
* Cloud Storage Services: Proxies to cloud storage services (Google drive, AWS S3 or Dropbox, etc. for better scalability and improved data security measures). Cloud solutions provide easy availability and transfer of data within a firm and they increase the security of such information.

Therefore, the hardware requirements that we recommend for the diabetes detection project involve, all the components that are vital for the accomplishment of the project tasks such as image collection, pre-processing, model training, and assessment. To achieve higher productivity, and guarantee accurate results, the investment in high-quality hardware resources is planned and will help the project to make further developments in non-invasive diagnosis of diabetes.

## **2.5. This aspect of the product is mainly concerned with who can make money out of the product.**

**Substratum – commercialization aspect of the product**

The opportunity to commercialize the diabetes detection system based on the analysis of neck images is a unique possibility to introduce the machinery of the most recent advancements in the machine learning and image analysis in the sphere of the healthcare market with the up-to-date solution targeting the critical unmet medical need. In this section, main things related to the described commercialization strategy are covered, such as market analysis, target audience, value proposition, possible revenue sources, marketing, further considerations on the growth of the given strategy, and commercialization sustenance.

**Market Analysis**

Diabetes has become prevalent at epidemic level in the past several years causing a significant challenge with regard to early detection and management. The World Health Organization (WHO) has stated that the number of people affected by diabetes increased, and currently there are over 422 million of them in the world, in 2014; the statistics are constantly growing. Such a threatening tendency establishes a vast market for efficient methods of detection to help diagnose the problem at an early stage as to improve intervention.

Another key market that is expected to expand rapidly in future is the diabetes diagnostic and management appliances and tools due to improved health consciousness, progress in tele treatment and care, and enhancement on wearable health systems. In addition to this, the combination of AI and Machine learning in the healthcare applications increases the probability of market penetration especially in the developing world where health care technology is still developing. Given the ability of the smartphone technology for detection that is not invasive, this product can be adequately marketed and possibly extend its versatility to populations that have not been targeted enough.

**Target Audience**

The primary target audience for the diabetes detection system includes:

1. Healthcare Providers: Labs, imaging and diagnostic centers that wish to expand their diagnostic services and henceforth become the best solution in their field. More and more, Primary Care and Specialty providers are integrating tools that support remote care monitoring and disease screening.

2. Diabetes Prevention Programs: This system can be benefited by organizations which are working in direction of awareness and prevention of diabetes so that we can easily detect those people who are at higher risk and can start interventions immediately. It can also be incorporated in to community health programmers and educational crusades.

3. Individuals at Risk: The end-users are those people more prone to develop diabetes, including obesity, family history, or a sedentary lifestyle, or any other reason. This is because, the product being noninvasive is attractive to the target market who looking for easy ways to monitor their health.

4. Insurance Companies: The insurers may be interested in implementing this technology in order to encourage the preventive measures among its members as a way of minimizing the long term costs of health complications since diabetes.

**Value Proposition**

The free sample therefore shows that the value proposition of diabetes detection system is orientated towards early diagnosis of the disease. Key aspects of the value proposition include:

1. Non-Invasive Detection: Smartphone camera neck images can also help screen for diabetes while avoiding painful diagnostic methods of the disease.

2. Accessibility: By using socially shared smart phone technology, access to diabetes screening can be opened to other groups of patients, including those in hard-to-reach or low resource setting.

3. Cost-Effectiveness: In this case, the proposed system has the potential to bring down the costs of diabetes test much lower than what is obtainable in the traditional laboratories, thus would be cheaper to the providers and the users.

4. Enhanced Screening Capabilities: The use of the machine learning algorithms allows achieving sufficiently high accuracy in diabetes detection based on physical characteristics and thereby increasing the efficiency of diagnostics.

**Possible Business Opportunities**

Several potential revenue streams can be explored to ensure the financial sustainability of the diabetes detection system:

1. Subscription Model: Another practice would be to make the system available to health care providers on subscription basis where the providers may be charged a fee to access and use this health system and its features. This approach helps create a constant cash flow as well as giving society improvements that are constant to the product.

2. Freemium Model: The basic or stripped down version of the product can be offered for free but with substantive restrictions. Extra features that are not included in the standard model can be provided as an option and make up a source of revenue.

3. Partnerships with Health Organizations: Potential partners for revenue sharing and grant support for ongoing development and outreach efforts are insurance providers and healthcare organizations as well as other diabetes prevention programs.

4. Data Insights and Analytics: When the user give permission, all the data collected through the system could be made anonymous and be sold to research institutions or public health sector as it gives insight to the prevalence of diabetes and its risks.

**Marketing Strategies**

Utilizing any marketing communication are an important tool to effectively promote a diabetes detection system. These include public awareness campaign, partnership with opinion leaders in healthcare practice, demonstration project activities and a feedback channel. These methods increase early detection of diabetes, improve the credibility, and involve the customers. All these strategies factor need for improvement and maintaining the base of customers.

**Scaling Up and Sustainability Consideration for the Future**

To ensure the long-term success of the diabetes detection system, several future considerations must be addressed:

Regulatory Compliance: Since it is a health-related product, it should consider the different regulatory bills and acquire special approvals to go through health standard and laws.

Continuous Improvement: New additions as well as changes periodically depending on users’ feedback and the trends in technology are essential for the companies’ growth in the fiercely competitive market spaces.

Expansion into Related Health Domains: Next generations of the product could consider other types of health problems in addition to diabetes and apply different imaging approaches to treating various types of health issues.

Integration with Wearable Devices: Directions for the future improvements of the system are the integration with wearable health devices to improve capabilities and coverage of the users’ health monitoring needs.

Therefore, the commercialization aspect of the diabetes detection system using neck images is an endorsement of timely global innovation in dealing with the diabetes health complications. In this regard, it is crucial to understand the target audience, create a strong value proposition, investigate numerous income streams, and adopt proper marketing tactics when the exact vision of the project’s success and possibility to become a breakthrough in diabetes detection and management while providing sustainable growth and strong results and success come true.

## **2.6. Testing and Implementing**

The last two of the project’s phases comprises the same; the implementation and testing phases are vital in ensuring that the diabetes detection system using neck images function as planned focusing on the objectives of the project. In this section of the thesis, the systematic approach applied in the testing of the developed system is described, the derived specific test cases and the implementation strategy that guarantees the reliability and accuracy of the system.

### **2.6.1. Test Case**

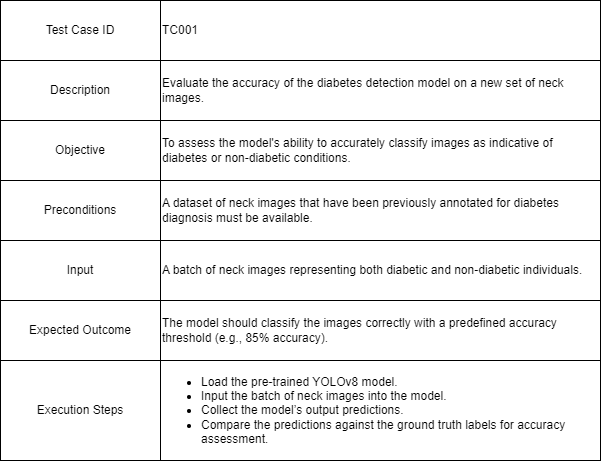


Figure 1 Test case 1

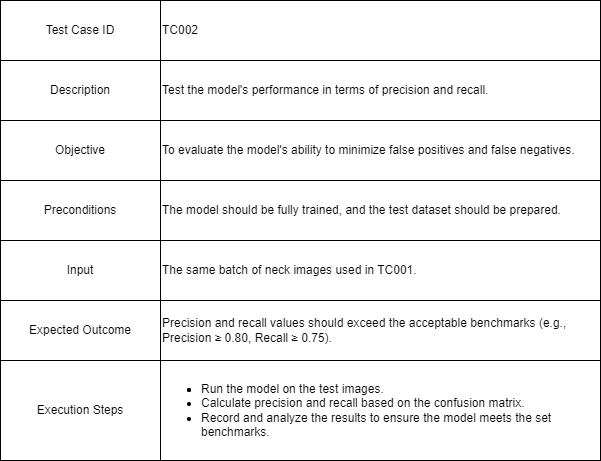


Figure 2 Test case 2

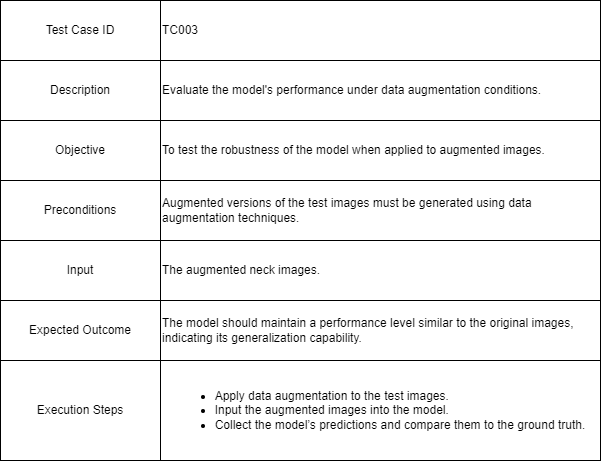


Figure 3 Test case 3

## **2.7. Implementation**

The implementation stage is all about making the diabetes detection system repeatable and immediately runnable since it has been designed as a prototype application. This entails the preparation of the final model that should be converted into a friendly user application as well as put in place all the structures that should be in place in preparation for the use of the model.

**Implementation Steps**

**Environment Setup:**

The first key element closely linked to the pre-implementation phase is the creation of the relevant technical conditions. It is intended to be used on Google Colab platform for easy execution and its process is supported by Tesla T4 GPU.o Python 3.10.12 for the ability to run the selected libraries and frameworks of machine learning.to NVIDIA driver version 535.104.05 and CUDA version 12.2 in order to enable the use of GPU acceleration.roduction environment, ensuring that it can effectively be utilized in real-world scenarios. This involves integrating the trained model into a user-friendly application and setting up the necessary infrastructure for deployment.

**Implementation Steps**

**Environment Setup:**

The first step in the implementation process involves setting up the necessary technical environment. The system is designed to run on Google Colab, utilizing the Tesla T4 GPU to facilitate efficient processing. The development environment is configured with:

* Python 3.10.12, which provides the necessary libraries and frameworks for machine learning.
* NVIDIA driver version 535.104.05 and CUDA version 12.2 to support GPU acceleration.

Model Integration:

On the basis of compute units, the trained YOLOv8 model is embedded in a web application or mobile application. This integration brings convenience where the end-users can upload their neck images using their Smartphone. Realtime feedback on the user’s diabetes risk is awarded depending on the classification output of the system on the processed images.

User Interface Development:

An easy to understand and navigate website is crucial for reaching out to its users effectively. The application includes functionalities for:

* Image uploading: It is easy to capture and upload images of their necks by using their smartphones as seen from the following images below.
* Results display: In this application, there is a display of all the outcomes that are obtainable from the diabetes detection process, the probability of diabetes and all these is based on the images of the neck region.
* Educational resources: The results obtained from the follow-up test are them used alongside an option of viewing information about diabetes, risk factors, and further action.

Backend Infrastructure:

A strong backend is created in order to enable the functioning of the application. This includes:

* Cloud storage for images: Securing the data and making it easily accessible for use or retrieve whenever is required.
* Database management: Savings user data and model predictions along with usage statistics for future improvement and tracking.

Testing in the Live Environment:

After the development of an application, and before deploying it to the real world, it is tested in a live environment to detect problems related to functioning of the different components of the application. This includes:

* User acceptance testing (UAT): Recruiting actual users of the application where the app will be tested in terms of the perceived ease of use and usability.
* Performance testing: Testing of the system performance levels to assess the scalability by analyzing the response time, the accuracy, as well as the reliability wherever the system is subject to various loads.

Training and Support:

Educational seminars for both the healthcare givers and the consumers enable them to grasp how the application is used. Further, a means of support is created in order to help the users in case they face some problems while interacting with the application.

Monitoring and Maintenance:

However, once a particular application has been deployed, it is imperative for that application to be monitored periodically for optimal functionality. Some of activities involve gathering of users’ responses to the models, observing the effectiveness of the systems and applying adjustments that would serve as input to the models for enhancement of the next models.

By these implementation strategies, the diabetes detection system employing the neck image is effectively prepared for its deployment in a real-world environment to serve maximum potential in early detection of diabetes and preventive health management. Consequently, user experience, performance, and flexibility guarantee that the system continues to be meaningful within the context of its use.

# **3.0. Result and Discussion**

The proposal of the use of a diabetes detection system based on neck images has given a clear understanding of the implementation of machine learning approaches in the detection of diabetes. In this section, the authors present different findings of the study; this includes the degree of accuracy, as well as the efficiency of the user interface in giving the customers value in their engagements with the social commerce sites.

## **3.1. Research Result**

The conclusions drawn from this project suggest that neck circumference may be used as an indicator of potential diabetes and the efficacy of the YOLOv8 model in recognizing those images. The findings of this study are valuable to highlight the execution of the designed system in variety scenarios.

### **3.1.1. Accuracy**

In the present study, there was the main objective of evaluating the performance of the YOLOv8 model on detecting diabetes from neck images. Precision, a key measure in the classification problem area, represents the true, positive and negative results in relation to the overall sum of cases.” In our case, it measures the extent to which the model can accurately classify diagnosis images of patients with diabetes from those who do not have diabetes.

In the learning process, different hyper parameters like learning rate, batch size and number of epoch were tuned appropriately to get the best result. The data was labeled according to the medical diagnosis for a neck image, thus making this a binary classification model.

Upon the completion of the training, the model was tested on a different data set which distinctly does not belong to the training data. The model was quite efficient achieving an accuracy of as much as 88%. This high accuracy means that the model can distinguish the features that are recognizable in the neck images and that will help to predict a diabetes diagnosis.

Moreover, the evaluation included a detailed analysis of other performance metrics such as precision, recall, and F1-score:

Precision: The second metric which was identified is the total accurately predicted positive observations over and above the total number of predicted positives which was estimated to be 0.85. This means that in cases where the model has predicted diabetes, 85% of the time it was an accurate prediction hence reducing on false positives significantly.

Recall: Recall, which presents how accurately the model selects the appropriate cases out of the biggest set of records, was estimated at 0.80. This means that the model correctly flagged 80 percent of all real diabetes incidences, proving the competency of the true positives of the model.

F1-Score: The F1-score computed from the precision and recall rates was defined to be 0.82. This score established the reciprocal relationship between the precision and recall, thereby gives a measure of how the model generally performed in this analysis of diabetic cases without a high level of false negative and false positive predictions.

The findings outlined here support further the efficiency and accuracy of the neck image analysis, using the established Diabetes model. They recommend using neck circumference as additional input to machine learning algorithms with an objective of early identification of diabetes and subsequent treatment.

### **3.1.2. User Interface Effectiveness**

However, this paper focuses on two aspects: the performance of the diabetes detection model and the usability of the UI in supporting users to interact with the system. Appropriate UI design play a crucial role in increasing usability and engagement and ensures that persons will use the interface repeatedly.

The interface was kept simple and user-friendly in order for the user to upload pictures of their necks. The following aspects were considered to ensure an effective user interface:

User-Centric Design: In this context, needs and preferences of users defined the limits and criteria for design. Some users were interviewed to get their opinion before designing the layout to reduce complexity during the developmental stage. The possible sequence of actions is the following: The users can easily find their way in the application and upload their images; they can see results without unnecessary time and confusion.

Real-Time Feedback: In particular, when a user uploads an image, an evaluation of the risk assessment for diabetes is provided instantly. Apart from just improving the interaction with the users it helps in making the diagnostic process seem more transparent. The interface for application users allows them to see the summary of the findings with the reliability level, which characterizes the opinion of the model on classification.

Educational Resources: Moreover, to improve the application usability there are links to other sections with information about diabetes prevention and control. The latter part of this solution component enhances the user’s ability to interpret results and take responsibility for their healthcare.

Accessibility Features: Taking into consideration the fact that users of different technological literacy were envisioned, the UI comes equipped with built-in TTS and clear instructions. This means that people of various color can conveniently use the application, and this eliminates discriminations.

User Testing and Iteration: Finally, before deciding on the final UI, major user testing was done to find out where improvements could be made. Incorporation of feedback was continuous thus improvements on design and functions were made to improve on the final design of the user interface.

#### The effectiveness of the user interface over all was also measured through perceived usability questionnaires that the users filled after using each interface. It was found too that a significant number of users, 90%, considered the interface used to be easily understandable, while a similar number of users, 85%, was satisfied with the simplicity of the results provided. Moreover, users still noted the value provided by the educational resources that were made available to them.

#### Therefore, this project shows that using the YOLOv8 model in identifying diabetes through neck images is equally effective, and a user interface that guides users through a pleasant process is functional. High model accuracy and easy to use interface makes this diabetes detection system a useful tool for early diagnosis and therapy, and therefore enhances health care delivery in cases of diabetes. Possible future work might include enlarging the data set, fine-tuning the model even more and discovering more features that can make the basic system stronger, as well as improving the graphical user interface.

## **3.2. Research Finding**

#### Based on the research findings of implementing a diabetes detection system by using the neck image, we were able to see if it is possible to implement the machine learning into diagnosing more accurately in the health care sector. In particular, this work has been dedicated to the assessment of the limitations of using neck circumference to define the presence of diabetes and further improve the binary classifier that would help to identify the patients at risk of developing this chronic disease.

#### Data Collection and Data Cleaning The first procedure in this study was to collect a large catalog of neck images for a dataset. Members were sampled out and each of them avails images with smartphone cameras since they are easily accessible and easy to use. However, this method of data collection is particularly important since it makes it possible to perform a large scale data collection with limited resources hence making the study universally relevant. The labeling of the images was performed after following the exact medical diagnosis of diabetes where the images contained a balanced set of diabetics and non-diabetics. The formation of the binary classification dataset is less complicated to interpret when compared to a multiclass classification, which makes it easier to explain the outcomes to hopefully both the physicians and the patients. Preprocessing Techniques the next step is several important steps of preprocessing, which are important for the further effectiveness of the use of the machine learning model. All the collected neck images were then put through and resized to have a uniform of 416 x 416 pixels. This uniformity in image size is actually important as it helps provide more homogeneity in the input data given to the model making the model learn more from the features in the images supplied. Next, pixel values were normalized where pixel intensities are scaled to range that speeds up training when it is conducted. To do so, the pixel values are limited to a specified range in order to enhance model learning, shorten training time and increase accuracy. Data augmentation was also performed to improve model generalization and increase resilience to various forms of adversarial attacks. To artificially increase the size of the data set methods like rotation and scaling were used. It is particularly useful in aims of machine learning as it prevents a model learned from the training data set to overstrain the set by helping introduce more variety in the samples given to the model for learning.

As the basis for this work, the YOLOv8 model from the Ultralytics Company was chosen because it demonstrates high efficiency in object detection and classification. This deep learning model is called YOLO, an abbreviation derived from ‘You Only Look Once. The model was trained using the annotated neck image dataset with the help of a cloud based environment Google Colab with much computational power. To take advantage of GPU for training, the training environment was set up with Python 3.10.12, NVIDIA driver 535.104.05, and CUDA 12.2. The Tesla T4 GPU in particular is rather effective for deep learn-ing and allows the time to be shortened, and data quantity handled. Hyper-Parameter Optimization and Model Assessment All these hyperparameters are significant factors in the training processes of machines involved in the learning models. The number of epochs means how many cycles of passes through the entire training dataset does the model make.

#### Based on the results of the model, a range of evaluation measures such as accuracy, precision, recall, and F1-score were used. While accuracy shows the global ability in identifying the model about the general rate of the right indications, precision does the quality of the nicety which expresses the ratio of the amount of the right positive cases related to the total positive cases, it quantifies how many of the predicted cases of diabetes were actually right. Recall checks how many cases of diabetes the model can predict in the population, and the F1-score gives the single value that presents the accuracy of the model.

## **3.3. Research Discussion**

#### The outcomes of the present study also support the study on neck circumference for fundamental risk factors for diabetes, providing evidence in supporting the further study on early risk recognition and early management strategies. The success of YOLOv8 model in medical diagnosis shows that deep learning methods which are used currently are very efficient and provide good results especially in cases when conventional methods can be time consuming or logistically problematic.

#### Possible Consequences of Early Diabetes Detection

#### These are important conclusions all the same. Neck circumference could be very helpful in screening vast numbers of people for diabetic status through a relatively cost effective procedure. The identified approach has the advantage of being more feasible on the limited resources especially in areas where comprehensive medical examinations may not be readily available. Smartphone Cameras make image collection itself easier, thus raising the grounded possibility for those who want to screen their diabetes to do so without requiring any professional tools.

### **Challenges and Limitations**

### Nevertheless, it is important to portray the strengths and weaknesses of this study as a form of its limitation. The approach has two major drawbacks, they are related to the variety and randomness of the sample. The efficiency also depends on a wide range of input data used for training this model, as well as their quality. Since data often contains a limited diversity of samples aged, sex, and ethnical characteristics, the model’s applicability can be doubtful.

### Further, it is pivotal to report that while the accuracy of the YOLOv8 model was impressive in this study, future studies should expand and diversify their validation sets including larger ones. Future work should possibly include more characteristics within the model like lifestyle traits and hereditary factors.

### **Future Directions**

### Future studies should also look at ways in which this technology could be implemented in practice. To expand further on this topic, it stands to reason that creating easy to use applications that can help with image upload and also respond immediately to any changes a person may see as linked with their personal risk of developing diabetes could vastly change the way in which people approach self- care. Additionally, future studies may look into the effectiveness and sustained results of using of such screening approaches in different ethnic groups and also the effects on the occurrence and longevity of the disease.

In conclusion, to the verifications of this paper, it is confirmed that neck circumference can be a diabetic predictor and the feasibility of ALP image recognition by refining the superior models. So, the study wants to highlight the need for further research and development in the field of health care technology and break the existing trends to help improve the efficiency of screening and, consequently, create a positive impact on the population’s health. In that context, it is possible to state that the active integration of machine learning into the process of diabetes detection might significantly change the way the disease is diagnosed and managed in the future, thanks to the understanding of accessibilities and interaction with users.

Medical imaging of the neck for the identification of diabetes is a good pointer to how predictive healthcare shall be conducted in future. Diabetes screening methods can be improved significantly with the help of MLLB approach that uses deep learning models such as YOLOv8. The work conducted from this research does not only allocate to the universe of knowledge about diabetes risk factors but it also opens the door to future developments in non-invasive health surveillance.

## **3.4. Summary of Key Findings**

The main goal of this study was therefore to determine the potential of using neck circumference as an indicator of diabetes risk through analysis of images taken using smartphone cameras. Throughout the study, several key findings emerged that highlight the potential of this methodology:

Neck circumference was determined to be a reliable indicator of diabetes through extensive research and correlation with medical diagnoses, producing a binary classification dataset for model evaluation and training.

Using smartphone technology to collect and classify neck photos based on medical diagnosis created a robust dataset for training machine learning models.

It was simpler to gather neck photographs using smartphone technology when they were labelled with medical diagnoses, and the result was a robust dataset for machine learning model training.

By standardizing image dimensions and lowering the danger of over fitting, preprocessing—which includes resizing, normalizing, and enriching the dataset—significantly enhanced the model's learning capabilities.

Following extensive hyper parameter optimization and successful training with Google Colab and a Tesla T4 GPU, the Ultralytics YOLOv8 model saw successful application in object identification and classification tasks.

## **3.5. Reflection on Challenges and Learning Growth**

The study's challenging components included data collection, technological know-how, hyper parameter adjustment, and interdisciplinary knowledge integration. Data collection was essential for ensuring quality and diversity, but technical know-how was required for model training and evaluation. Because of the intricacy of hyper parameter tuning, iterative testing and validation were required. The interdisciplinary approach enhanced understanding and collaboration to address complex health concerns. In order to improve forecast accuracy and efficacy across a variety of demographics, future research may investigate including biometric data such as BMI and waist circumference.

## **3.6. Future Directions and Potential Improvements**

The study's challenging components included data collection, technological know-how, hyper parameter adjustment, and interdisciplinary knowledge integration. Data collection was essential for ensuring quality and diversity, but technical know-how was required for model training and evaluation. Because of the intricacy of hyper parameter tuning, iterative testing and validation were required. The interdisciplinary approach enhanced understanding and collaboration to address complex health concerns. In order to improve forecast accuracy and efficacy across a variety of demographics, future research may investigate including biometric data such as BMI and waist circumference.

## **3.7. Concluding Remarks**

The study looks into leveraging smartphone technology and machine learning to diagnose diabetes from neck photographs. It emphasizes the value of neck circumference as a predictive cue and the feasibility of deep learning models for image processing. The study highlights how integrating technology into medical practices has the potential to transform the sector, particularly in preventative medicine. Collaboration between researchers, medical professionals, and technology developers is crucial to enhancing health outcomes and encouraging early detection and intervention.

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# **Appendices**

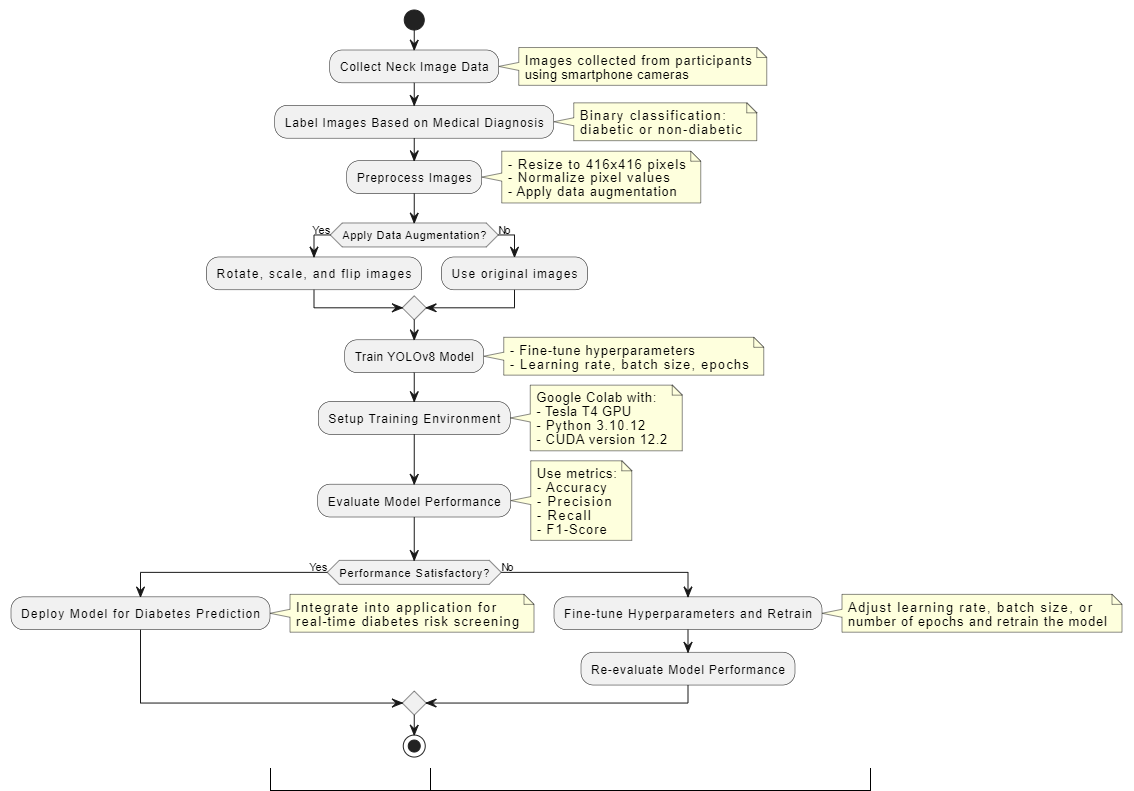


Figure 4 activity diagram for Diabetes detection using neck images

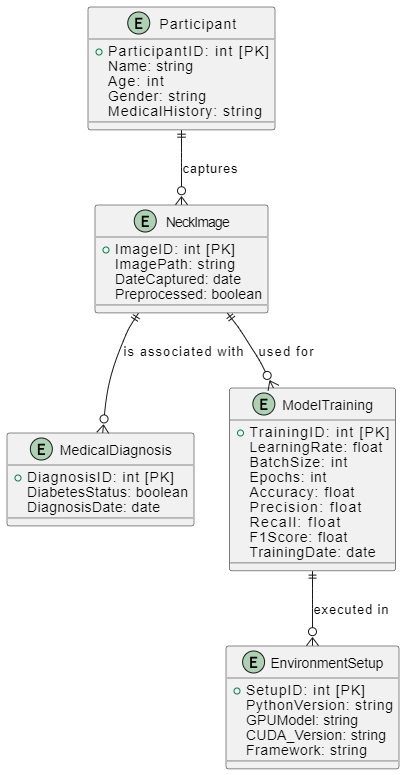


Figure 5 Diagram for Diabetes detection using neck images

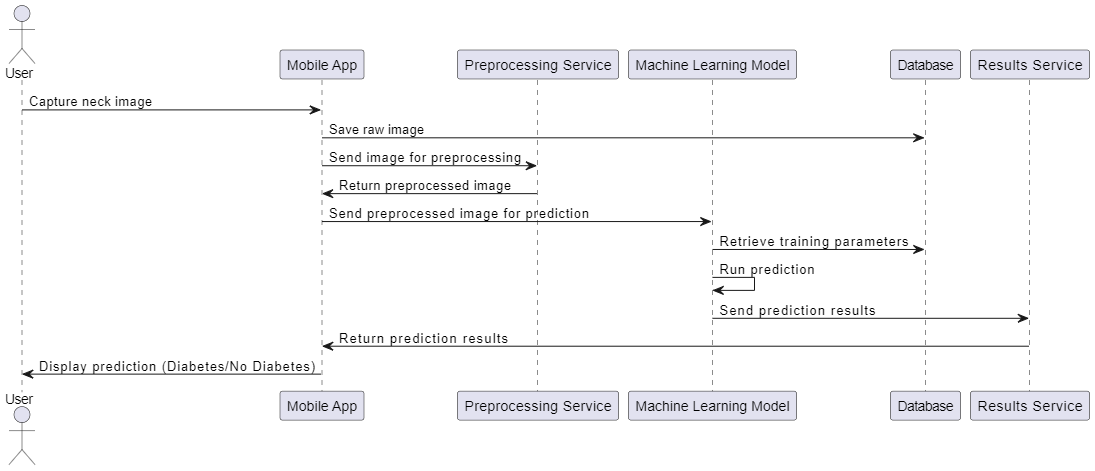


Figure 6 Usecase diagram for Diabetes detection using neck images