Machine Learning Algorithm Using Diabetic Detection Based On Tongue Images

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***Abstract*— In today's the world at large, the tongue key role in human communication and overall health. It is intricately connected to various parts of the body, making it an important indicator of overall well-being. One fascinating application of tongue analysis is in the field of diabetic classification. This project focuses on detecting diabetes using tongue images through the extraction of texture attribute and employing Convolutional Neural Network (CNN) attribute. The process begins by inputting tongue images, which are then subjected to global feature extraction to capture relevant characteristics. Subsequently, CNN classifiers are utilized for the classification task. This method showcases the potential of using non-invasive and easily accessible imaging techniques for medical diagnosis and monitoring. In day to day an artificial intelligence and machine learning methods is more used with the diagnosis of diseases. In this paper, the reference data is used by Diabetes Diagnosis Data to evaluate the proposed method. This method used with the help from the auto-encoder neural network is of a deep network built made in two ways. In the first method, Auto encoders are a type of neural network used to learn efficient codings of unlabeled data. autoencoders might be used to preprocess and reduce the dimensionality of the data related to the disease diagnosis, extracting relevant features that are critical for accurate diagnosis. In the second method, evaluated with the help of the final learning machine and the deep network has been constructed. This machine might take the outputs from the deep network as inputs and apply additional learning algorithms (like support vector machines or decision trees) to enhance prediction accuracy.**

***Index Terms*— Diabetes detection, CNN, Auto-encoder neural network, back propagation delay, final learning machine, Support vector machine.**

INTRODUCTION

1. Machine Learning Technology

Machine learning is a branch of artificial intelligence and computer science that involves using data and algorithms to mimic the way humans learn, progressively enhancing accuracy with experience. Machine learning algorithms construct mathematical models capable of making predictions or decisions without explicit programming, relying on sample data, often referred to as labeled data. This field combines principles from statistics and computer science to build predictive models, utilizing algorithms that learn from historical data.

The quality of the information provided is directly proportional to the performance of the machine learning model. The concept of machine learning covers both basic and advanced techniques, suitable for both experienced professionals and students. It delves into various methodologies, encompassing supervised, unsupervised, and reinforcement learning, offering a robust primer on the basics of machine learning. Machine learning, a subset of artificial intelligence, concentrates on enhancing system performance through data analysis. Artificial intelligence denotes machines demonstrating human-like intelligence. Although machine learning and AI are frequently linked and used interchangeably, they differ. It is crucial to recognize that not all AI encompasses machine learning, yet all machine learning constitutes a type of AI.

2. Image Processing Technology

Indeed, image processing is a rapidly evolving field that has seen significant advancements over the years. Today, many organizations across various sectors utilize image processing Image processing finds utility in diverse applications, such as visualization, image data extraction, pattern recognition, classification, segmentation, and beyond. The two primary methods of image processing are analogue and digital. Analog image processing is typically applied to hard copies of images, such as printouts and scanned photos. The outputs of analogue processing are usually images themselves. Digital image processing is a popular method for manipulating digital images using computers. It allows for the extraction of various types of information from images, such as feature data, characteristics, bounding boxes, or masks. This approach enables precise image manipulation, which is beneficial in various industrial applications.

3. Working of image processing in Machine Learning

Machine learning models generally follow a systematic approach to extract patterns and insights from data, applicable across various domains, including image processing. For effective image manipulation tasks, it's essential that the training images are ofhigh quality and properly prepared, complete with precise annotations. Computer Vision (CV) plays a key role in this area, as it is dedicated to developing systems that can comprehend and analyze visual information. In essence, CV empowers machines to interpret and act upon image data, which is crucial for successful application in image-based tasks.

II. LITERATURE, COLLECT IDEA AND RESEARCH

It is essential to conduct digital image processing as a preliminary step before proceeding with research work writing. This process involves a thorough thought process about your journal research and subject, ensuring that you have a complete understanding of the topic for it is viability by following means:

1. Chinese Traditional medical diagnosis of the tongue by computerized image analysis based on a novel approach

We have noted a dose-response relationship between an increased risk of developing diabetes and higher resting heart rate, impaired fasting glucose (IFG), and the progression from IFG to diabetes. This association remains significant even after adjusting for potential confounding factors.

2. Using Tongue mage by feature Selection Method for Health Identification

A feature groups A, B, and C are taken from 27 features. Group A and group B are divided into seven features, while 25 feature were selected from groups A and C.

3. Diabetes Mellitus Among Japanese Non-smoking Women and Men is Associated with Yellow Tongue Coating

In traditional East Asian medicine, a yellow coating on the tongue is often noted as a clinical sign of diabetes mellitus. This indicates that variations in the tongue's appearance, such as the presence of a yellowish layer, are used in this medical tradition to signal potential diabetes.

4.Diagnostic of Diabetes Method Based on Support Vector Machine

Employing a genetic algorithm (GA) to fine-tune the parameters of a Support Vector Machine (SVM) has significantly boosted the accuracy of diabetes detection during training. This approach has raised the accuracy from about 72% to 83.06%, demonstrating the efficacy of integrating SVM with GA to enhance diagnostic precision in detecting diabetes.

5. Examining and identifying tongue texture characteristics within an extensive database is crucial for numerous medical and diagnostic applications. Assessing the texture of the tongue provides important information about an individual's health and possible medical conditions. This analysis involves employing sophisticated imaging technologies and algorithms to detect and categorize subtle differences in tongue texture, which can be leveraged for diagnostic assessments..

A non-contact colorimetric imaging system was developed to capture over 9,000 tongue images with a digital camera. These images were utilized to establish the color spectrum of the tongue within the CIE chromaticity diagram. To accomplish this, a new color range boundary descriptor was implemented, incorporating a one-class Support Vector Machine (SVM). This method facilitates a thorough analysis of the color range and distribution observed in the tongue images, offering valuable information for applications in health monitoring and diagnostics.

6. To enhance diagnostic precision in recognizing sinusitis from paranasal sinus X-rays, multiple deep learning models were employed. This approach aims to improve the accuracy of detection and diagnosis by leveraging the strengths of various deep learning techniques.

For the initial evaluation of paranasal sinusitis, sinus X-ray imaging remains a widely used diagnostic tool. This method focuses on detecting air or fluid levels and areas of opacification in the sinuses, which are most clearly observed in the Waters' view of the paranasal sinuses (PNS). This imaging approach assists in revealing signs of inflammation or infection within the sinuses, contributing to the diagnosis and treatment of sinusitis.

7. In diagnosing diabetes mellitus through tongue examination, a key factor is assessing blood stasis. This assessment looks for signs on the tongue that suggest inadequate circulation or blood stagnation, which may be linked to diabetes and its related complications.

The presence of bluish discoloration on the tongue, along with petechiae (small red or purple spots resulting from subcutaneous bleeding) and swollen sublingual collateral vessels, can indicate blood stasis. This is particularly relevant in diabetic patients, as blood stasis can exacerbate the risk of vascular complications. To better understand the underlying physiological mechanisms of these complications, further research is needed to explore the connection between Heart Rate Variability (HRV) and blood stasis.

The study aimed to investigate the relationship between type 2 diabetes mellitus (DM) and blood stasis by analyzing tongue images. The research focused on identifying potential correlations between HRV patterns and diabetes status and assessing the practicality of using tongue imaging as a non-invasive method to evaluate blood stasis. This is crucial given the role of blood stasis in diabetic patients and its implications for vascular health. The images used for this study were captured at a resolution of 300 dpi, 8 bits per pixel in grayscale, and saved without compression.

8. A Smartphone application for self-management, based on Research Kit, was developed for patients with type 2 diabetes and prediabetes. The app allows users to monitor their gluconate usage patterns.

Slowing the progression of diabetes and preventing the transition from prediabetes to diabetes are critical global health challenges. Studies have demonstrated that mobile health (mHealth) interventions can be highly effective in supporting self-management for patients with type 2 diabetes. mHealth offers patients convenient access to tools and resources, improving the efficiency of healthcare delivery and empowering individuals to take control of their health. The availability of numerous healthcare apps provides patients with a variety of options for managing their health. The effect of these apps on health outcomes is not fully clear, particularly when images are slightly resized or adjusted without professional medical oversight. Gaining insight into how these apps are used could enhance their effectiveness and user experience for people managing diabetes.

III **PROPOSED SYSTEM**

Diagnosis is a fundamental process in determining the disease or condition based on a person's signs and symptoms, as depicted in Fig 1. This block diagram outlines a process for diagnosing medical conditions using tongue images.

- *Tongue Image Acquisition*: The first step involves capturing images of the tongue.
- *Image Segmentation*: The acquired images are then segmented to isolate the relevant parts for analysis.
- *Feature Extraction*: Specific features from the segmented images are extracted for further analysis.
- *Texture Analysis:* The texture of the tongue is analyzed to identify any abnormalities.
- *Color Analysis:* The color of the tongue is also analyzed as it can indicate various health conditions.
- *Diagnosis Results*: Finally, the results from the feature extraction, texture analysis, and color analysis are combined to provide a diagnosis.

This methodical approach leverages digital image processing techniques to assist in medical diagnosis, which can be particularly useful in telemedicine or automated diagnostic systems. This process is commonly referred to as "making a diagnosis" in the medical field. To make a diagnosis, healthcare providers typically collect information through a physical examination and a detailed medical history. In certain situations, additional diagnostic tests may be required. Posthumous diagnosis, which is performed after a person's death, is also recognized as a type of medical diagnosis. This method is crucial for identifying the cause of death and can be utilized for research or legal purposes [1].

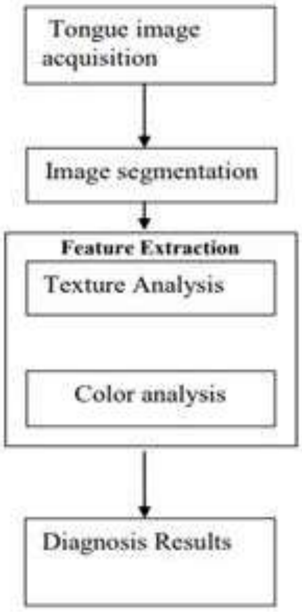


Fig:1 Flowchart of Diagnosis

A. Workflow of CNN Results and Discussion

To identify diabetes, the project starts by using a global feature extraction technique on tongue images. The color differences found in these images can be used to predict the likelihood of diabetes in patients. As shown in Fig 2, the use of tongue images for diabetes detection is effective, illustrating how the visual characteristics of the tongue can aid in identifying potential diabetic cases [2].

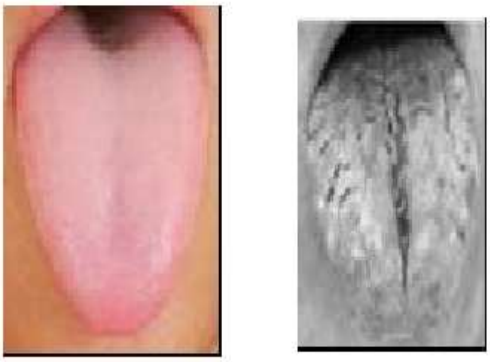


Fig 2 Tongue image of Normal Visible

Fig 3 Tongue image of Abnormal vision

The first phase of detecting diabetes involves using a global feature extraction technique on tongue images [3]. This approach centers on examining color variations across various tongue images, as these differences can suggest the presence of diabetes in individuals. Fig 3 showcases how this method performs in identifying diabetic cases by analyzing tongue images, emphasizing its potential as a diagnostic tool [4] [5]. Additionally, Fig 4 displays the different channel images of the tongue.

Fig 4 Different channels Normal Visible image of Tongue

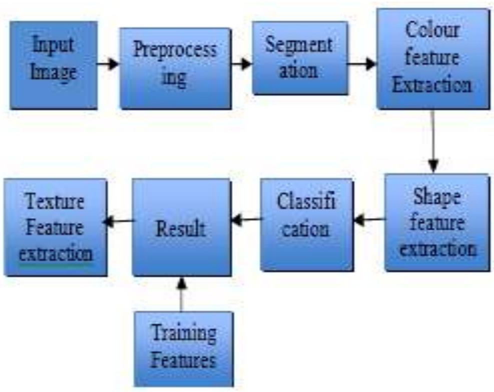
Performance analysis of diabetes detection using visible tongue images:
The initial phase of the system involves utilizing global features for extraction from the tongue images [6]. These features are essential for detecting color variations that may signify diabetes in individuals. The concluding phase utilizes Convolutional Neural Networks (CNNs) for the classification process. Table 1 illustrates the performance metrics of the proposed system, highlighting its efficacy in diagnosing diabetes through tongue image analysis.

TABLE 1. DIABETIC DETECTION PERFORMANCE USING TEXTURE FEATURES AND RFC

	Accuracy (%)	Sensitivity (%)	Specificity (%)
Normal visible images	95	94	93
Abnormal Images of Tongue	93	92	91

Table 1 presents significant results from the analysis. For normal tongue images, the classification accuracy is notably high at 95%, with sensitivity and specificity rates of 94% and 95%, respectively. On the other hand, for abnormal tongue images, the classification accuracy is 93%, accompanied by sensitivity and specificity rates of 92% and 91% [7]. These findings highlight the effectiveness of using global features combined with CNNs for accurately identifying diabetes through tongue image analysis.

IV.BLOCK DIAGRAM



Preprocessing:

Preprocessing is a crucial step in image processing and feature extraction. It involves preparing the input image for further analysis by enhancing its quality and making it more suitable for segmentation and feature extraction. Here are some common preprocessing techniques:

- *Noise Reduction*: Removing unwanted noise from the image to improve clarity. This can be done using filters like Gaussian or median filters.
- *Contrast Enhancement*: Adjusting the contrast of the image to highlight important features. Techniques like histogram equalization can be used.
- *Normalization:* Scaling the pixel values to a standard range, often between 0 and 1, to ensure consistency in further processing steps.
- *Smoothing:* Blurring the image slightly to reduce minor variations and focus on larger structures. This can be achieved using smoothing filters.
- *Edge Detection*: Identifying the edges within the image to highlight boundaries and important structures. Common methods include the Sobel or Canny edge detectors.

Preprocessing helps in improving the quality of the image, making it easier to segment and extract meaningful features in the subsequent steps.

1.Working Principle of Block Diagram

Diabetes is a chronic illness marked by high blood glucose levels due to either inadequate insulin production or the body's poor response to insulin. Early detection is essential, but Traditional Chinese Medicine often depends on subjective methods, which can be inconsistent and unreliable [20]. This research presents a portable device created using a Raspberry Pi 3 Model B and programmed in Python 3. The device employs a Convolutional Neural Network (CNN) to diagnose diabetes mellitus [8]. It was trained with datasets of tongue images from both diabetic and non-diabetic individuals. To evaluate the performance of the device, a confusion matrix was employed to examine misclassifications, especially cases where a diabetic tongue was incorrectly identified as non-diabetic. The device recorded a misclassification rate of 12% and a precision rate of 92.6%, yielding an overall accuracy of 88%. These findings highlight the promise of CNN-based devices for reliable and effective diabetes detection [9].

2. *Measurement methodology*

Tongue thermograms were obtained from participants using an infrared camera (FLIR A305 SC, FLIR Systems, USA). To ensure precise measurements, participants were asked to remove any metallic items and acclimate to a controlled environment with a temperature of 22–23°C and 50% relative humidity. Prior to image capture, participants rested in a relaxed posture for ten minutes. During the fasting state, tongue images were collected from all subjects. Participants were positioned with their chin on a support and directed to extend their tongue downward before the images were taken. They were advised to close their mouth after two minutes to avoid prolonged extension, which could affect blood perfusion and tongue surface temperature. Thermal images were captured at a distance of 0.3 meters from the tongue region using the thermal camera. FLIR Tools software was used to analyze the tongue thermograms, maintaining a constant temperature scale and FLIR Tools is a software suite designed for analyzing and reporting data from FLIR infrared cameras. A template of the tongue was created, with a region of interest (ROI) fixed on the tongue. The central region of the tongue was identified as corresponding to the stomach and spleen organs in the human body.

3.Methodology:

Deep Convolutional Neural Network:

Traditionally, Machine learning algorithms and data mining algorithms are typically developed to address specific problems in isolation. These algorithms are trained on a particular feature space and distribution [17]. In specific tasks, models are trained using a machine learning algorithm based on the business case. However, A common assumption in machine learning is that the training and test data must have identical feature spaces if features and distributions change [11]. However, this assumption may not hold true, sometimes necessitating models to be rebuilt from scratch. Rebuilding models and collecting new training data can be a time-consuming and challenging process. In such scenarios, transfer learning becomes a desirable approach. Transfer learning involves transferring knowledge from pre-trained models to new tasks or domains.

This method allows for the reuse of pre-existing knowledge, which can be applied to regression, classification, and clustering problems [12]. This paper specifically employs transfer learning with One of the pre-trained models used is VGG-16, which employs a Deep Convolutional Neural Network to classify images based on their underlying distribution. By leveraging the pre-trained model's knowledge, the authors aim to enhance the performance of their classification task without the need to start from scratch [18].

Fig 5 illustrates In conventional machine learning, different learning systems are trained separately for disparate tasks. In contrast, transfer learning extracts knowledge from a source task to a target task, especially when the latter has limited labeled data for supervised learning [13].

For instance, consider a problem of identifying objects in images within a constrained domain space of Region 1 (R1). Initially, we train a machine learning model and collect a dataset for the domain space (R1) to extract features and make predictions on test data [14]. This model performs well on test data points that are tuned from the same domain space of Region 1 (R1). However, the main limitation arises when traditional deep learning algorithms are used without sufficient training data for the required tasks in domain space Region 1 (R1), resulting in underperformance [15].

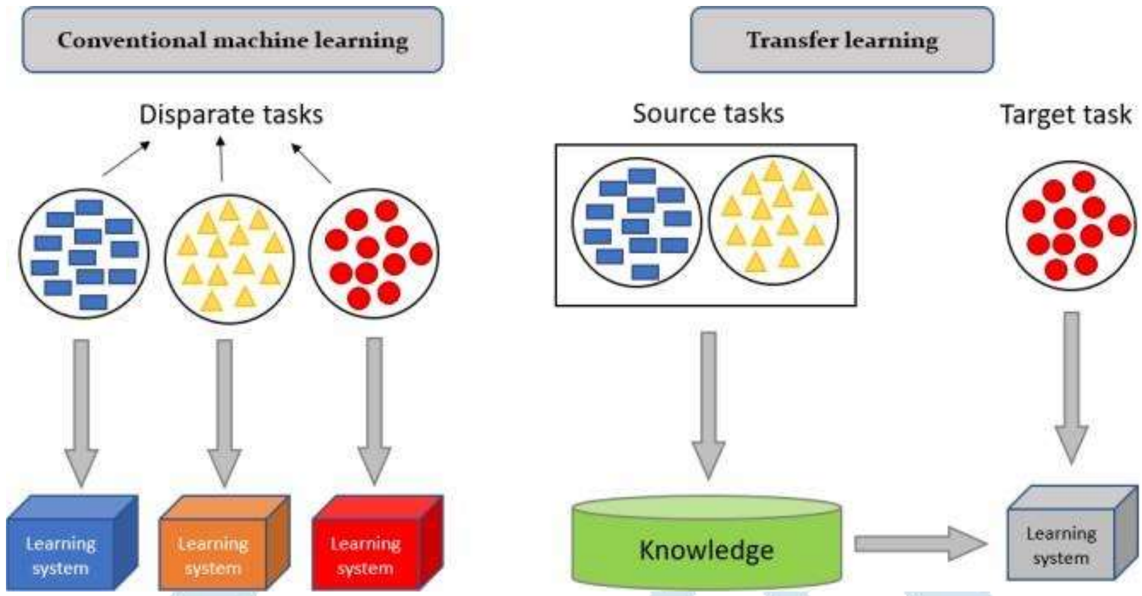


Fig 5.Learning Processes between Transfers Learning And Conventional Machine Learning

The image you shared compares Conventional Machine Learning with Transfer Learning.

Conventional Machine Learning
Separate Learning Systems: Each task is learned independently, requiring its own learning process from scratch Transfer Learning
Source Tasks: Knowledge is gathered from multiple source tasks.
Target Task: This knowledge is then transferred to a new, different task.
Shared Learning System: The learning process for the target task benefits from the pre-existing knowledge, making it more efficient.

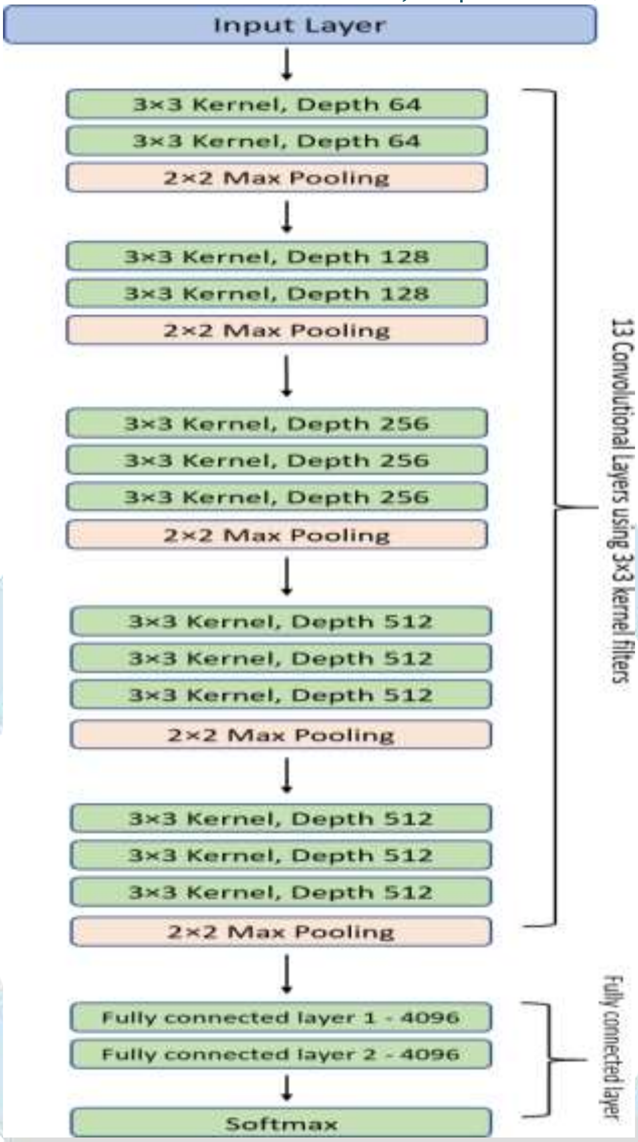


Fig 6.Conventional Layer

A Convolution Neural Network (CNN) is a type of artificial neural network that uses multiple perceptions to analyze image inputs. The Fig 6 shows the conventional layer model. It consists of learnable weights and biases that are applied to different parts of images, enabling it to differentiate between them [16]. One of the advantages of using CNNs is that they require CNNs have fewer weights compared to fully connected networks because some parameters are shared. This characteristic enables CNNs to leverage local spatial coherence in input images, making them highly effective for image classification tasks.

V.RESULT AND DISCUSSION

The Training codes give the output for the tongue in the dataset and provide the accuracy value for the process. Fig 7 shows the dataset output.

1.Color Analysis

Predominantly Pale with Patches of Red: The tongue is primarily pale, which can be an indicator of poor blood circulation or anemia, common in diabetic patients. The patches of red may suggest inflammation or infection, which can also be associated with diabetes.

2. Texture Analysis

Rough Texture with Visible Cracks: A rough tongue surface with cracks can be a sign of dehydration or a nutritional deficiency, both of which are common in diabetic individuals. This texture can also indicate the presence of oral thrush or other fungal infections, which are more prevalent in people with diabetes due to a weakened immune system.

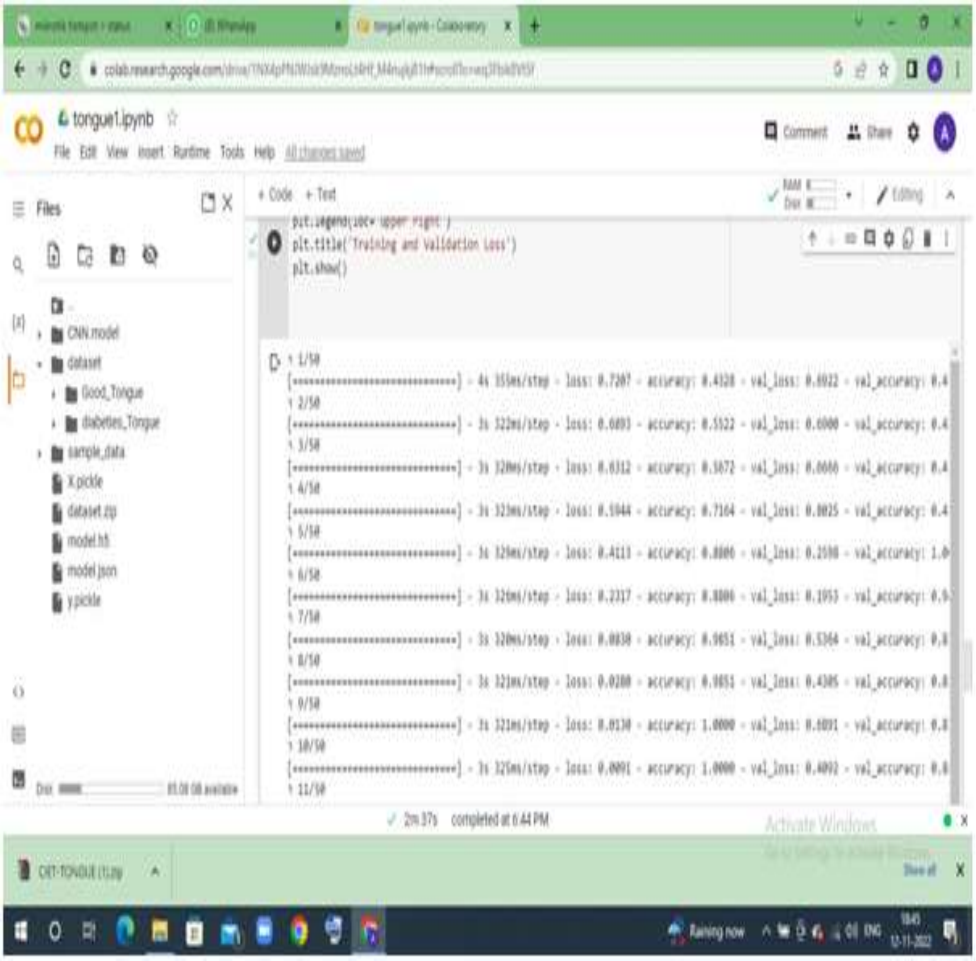


Fig 7.Dataset Output

3. Geometry Analysis

Enlarged Tongue with Irregular Edges: An enlarged tongue, also known as macroglossia, can be a symptom of conditions like hypothyroidism, which often co-occurs with diabetes. Irregular edges could be due to dental impressions or other underlying health issues.

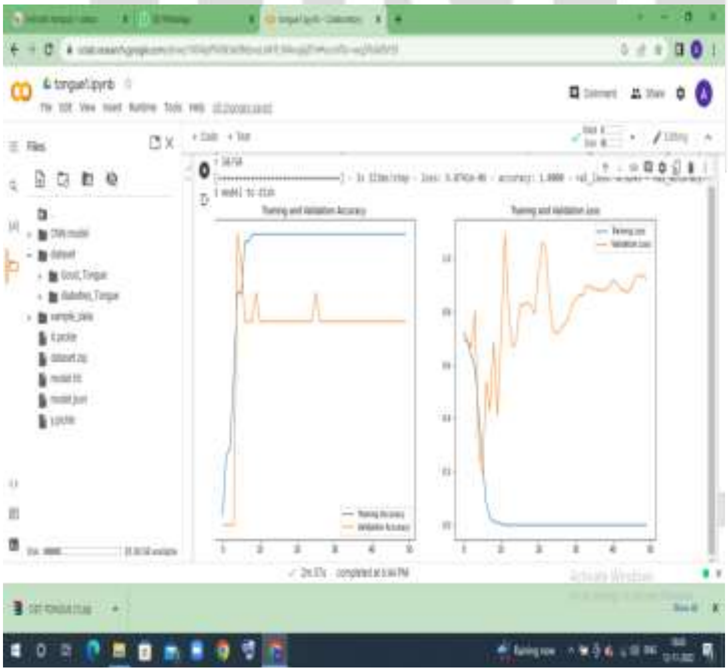


Fig 8.Graphical representation of output

- The trained code also provides the graph representing the values of the trained images. Fig 8 illustrate the graphical representation of tongue image output.

In this representation:

- The **Color Analysis** table shows predominantly pale cells with some red patches, indicating the color distribution on the tongue.

- The **Texture Analysis** table represents rough textures with visible cracks.
- The **Geometry Analysis** table indicates the tongue's enlargement and irregular edges.
- The **Classification Result** shows a high confidence of 92% for diagnosing diabetes.

VI. Conclusion

The analysis of tongue images for diabetes detection has yielded significant insights:

Color Analysis: Predominantly Pale with Patches of Red: The tongue's pale color suggests poor blood circulation or anemia, common in diabetic patients. The red patches might indicate inflammation or infection, which can also be associated with diabetes.

Texture Analysis: Rough Texture with Visible Cracks: A rough surface with cracks on the tongue can be a sign of dehydration or nutritional deficiency, both prevalent in diabetic individuals. This texture can also point to oral thrush or other fungal infections, more common in people with diabetes due to a weakened immune system.

Geometry Analysis: Enlarged Tongue with Irregular Edges: An enlarged tongue, known as macroglossia, can be a symptom of conditions like hypothyroidism, which often co-occur with diabetes. Irregular edges could be due to dental impressions or other underlying health issues.

Integrated Conclusion

Non-Invasive Diagnostic Potential: The combined analysis of color, texture, and geometry of the tongue offers a promising non-invasive method for diabetes detection. This approach can provide a convenient alternative to traditional diagnostic methods.

Early Detection and Monitoring: By identifying key markers associated with diabetes, this methodology can facilitate early diagnosis and ongoing monitoring of diabetic patients, potentially leading to better management and treatment outcomes.

Future Directions: Further research with larger and more diverse datasets, integration with other diagnostic tools, and the development of personalized models can enhance the accuracy and reliability of this diagnostic approach.

VII. FUTURE SCOPE

Using Convolutional Neural Networks (CNNs) for diabetes-related applications poses two primary challenges: a limited dataset and the potential for overfitting. These issues can be mitigated by broadening the feature set and applying strategies designed to address these challenges. Gaining a thorough understanding of CNNs—including their benefits and limitations—is essential to effectively leverage their capabilities in diagnostics. The ultimate aim is to improve the accuracy of diabetes detection and enhance patient care.

To address the issue of a small dataset, future research will focus on expanding the dataset size. This increase will not only provide additional training data for the CNN but also help reduce overfitting by allowing the model to better generalize to new, unseen data. Furthermore, techniques such as data augmentation, transfer learning, and regularization will be utilized to further improve CNN performance in diabetes detection tasks.

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