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AN INTELLIGENT NON-INVASIVE GLUCOSE MONITORING SYSTEM USING HISTOGRAM FEATURES, SVM AND ADAGRAD OPTIMIZATION

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ABSTRACT

With the use of cutting-edge technologies like machine learning and image processing, medical diagnostics and healthcare have evolved significantly in recent years. One of the many uses of these technologies is the analysis of glucose content, which is crucial for managing and tracking diabetes and other metabolic conditions. With the development of non-invasive imaging techniques, a new range of options has emerged for glucose level analysis, offering patients safer and more practical choices. The aim of this paper is to assess glucose levels based on digital picture identification using the MATLAB application for patient glucose data processing. For diabetics, joint injections are used to regulate blood sugar levels. The body may sustain small physical damage from repeated injections, which may impair the immune system's capacity to combat infections. Urine-based non-invasive glucose testing has been the focus of numerous studies. In order to investigate the non-invasive glucose testing process, this study was developed using image processing. For image database extraction, the noise is reduced using a Gaussian filter and histogram-based feature extraction. Support vector machines use 70% training and 30% testing approach to classify data. The SVM classification results took 0.5 seconds to process and had an accuracy of 85%. The effects of diabetes, pre-diabetes, and non-diabetes can be taken into account while making medical decisions. Furthermore, by dynamically modifying the learning rate for every feature, the Adaptive Gradient (Ada Grad) optimization algorithm is integrated to improve the classification model's learning efficiency. By increasing convergence speed and overall prediction stability, this integration helps to classify glucose levels more accurately.

Keywords: Glucose Content, Gaussian Filter, Histogram Extraction, Adaptive Gradient (Ada-Grad) Optimization

I. INTRODUCTION

A vital sign of a person's health, glucose is the body's main energy source. Blood glucose levels are directly related to metabolic diseases, including diabetes mellitus. To avoid acute complications and reduce long-term health hazards, diabetes care requires accurate and timely glucose monitoring. In the past, blood glucose levels were determined by blood sample, which was an uncomfortable and invasive procedure that made it challenging for patients to receive frequent monitoring. Non-invasive imaging techniques including thermal imaging, hyper spectral imaging, and near-infrared spectroscopy (NIRS) have become popular in the context of glucose content monitoring because they can yield useful information without requiring blood samples. Because it can correctly monitor glucose concentrations and penetrate biological tissues, near-infrared spectroscopy is especially promising. To extract pertinent elements, such spectral information and spatial patterns, from the collected images, image processing methods are used. These characteristics allow for the creation of precise and reliable predictive models by acting as input data for machine learning models. A state-of-the-art method of assessing glucose levels, usually done using blood tests or urine analyzers, is glucose content analysis using image processing.

Figure 1: Glucose Monitoring System

II. LITERATURE REVIEW

A. Yudhana et.al [1], has created a portable gadget that incorporates the AMG 8833 series' IR thermal sensor for real-time self-health monitoring. The suggested study uses a non-invasive method to determine the degree of glucose and dehydration based on the temperature of a urine sample.

F. A. Khan et.al [2], have been created in this field for the classification, prediction, and detection of diabetes. Millions of individuals worldwide have been impacted by diabetes, one of the chronic diseases with the fastest rate of growth. Crucial are its diagnosis, prognosis, appropriate treatment, and management. Forecasting methods based on data mining for diabetes data analysis can aid in the early identification and prognosis of the condition as well as associated crucial events like hypoglycemia and hyperglycemia.

M. F. Rabbi et.al [3], has evolved to compile all of the conclusions and suggestions made by earlier research that looked into the use of EMG in the diagnosis of diabetic neuropathy. One of the physical side effects of diabetes mellitus (DM) in patients with a lengthy history of the disease is diabetic neuropathy. Diabetic neuropathy may benefit greatly from an evaluation based on electromyography (EMG).

M. S. DIab et.al [4], have been created and applied to categorize and forecast an individual's risk of developing diabetes. It offers three neural network-based models for diabetes prediction and classification. These models consist of a cascade forward architecture, a feed forward network, and a pattern network. The accuracy, sensitivity, and specificity of the three models' performances are contrasted.

III. ADAPTIVE GRADIENT (ADA-GRAD) OPTIMIZATION

In the field of deep learning and machine learning, it is crucial to optimize a model's parameters in order to obtain accurate and useful results. To enhance training and accelerate convergence, several optimization techniques have been developed. One such technique is AdaGrad (Adaptive Gradient technique), which modifies each parameter's learning rate according to its previous gradients. Adagrad is useful for sparse data and variable feature magnitudes since it scales updates using previous gradients, in contrast to normal gradient descent, which has a constant rate. The primary concept behind Adagrad is the idea of adapting the learning rate based on the historical sum of squared gradients for each parameter. Similar to other optimization techniques, Adagrad starts by randomly initializing the parameter values. For each parameter, it also initializes a running total of squared gradients that will be used to track the gradients over time. Similar to ordinary gradient descent, the gradient of the loss function with respect to the parameters of the model is computed at each training step. The main distinction follows. Adagrad uses the accumulated sum of squared gradients to modify the learning rate for each parameter rather than employing a preset learning rate. Because it increases training efficiency and prediction accuracy, adaptive gradient (AdaGrad) optimization is crucial to machine learning-based glucose content analysis. It is useful for diabetes monitoring and intelligent healthcare systems because it excels at processing high-dimensional biomedical data, including spectroscopic measurements and glucose sensor inputs.

IV PROPOSED APPROACH

The proposed approach for glucose content analysis using image processing follows a structured and efficient methodology to ensure accurate classification. Initially, the input image is acquired and preprocessed using a Gaussian filters to remove noise and enhance image quality. From the filtered image, significant statistical features such as mean, standard deviation, variance, and skewness are extracted to capture intensity distribution characteristics. These extracted features are then fed into a

Support Vector Machine (SVM) model for classification. Finally, the system produces the classified output, indicating the predicted glucose level category with improved accuracy and reliability.

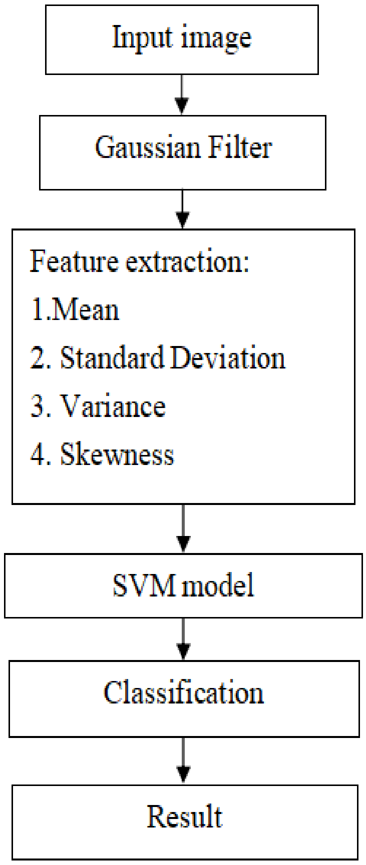

Figure 2: Proposed Machine Learning Framework for Image-Based Glucose Level Classification

Preprocessing

To gather glucose images for database retrieval, an optical camera with a 1920x1080 pixel resolution and a high-quality 2.8–12mm manual various CS lens was utilized. To give the user the greatest number of color options, the image was cropped to 2 cm by 2 cm. The PNG format is utilized when making images. There is a lot of noise in the urine strip's hue. The first step is to manually remove glucose pictures from urine strips in Adobe Photoshop, as shown in Figure 3.

Figure.3: Cropping Image Glucose

Filtering Gaussian

Applying a gaussian filter to remove noise and get a lot of texture in the image. Gaussian filters are commonly represented as two-dimensional arrays [x, y]. The gaussian matrix element G(x,y)=G(x,y), situated at position [x, y], represents the standard deviation, or sigma. The gap between distant or weak pixels (noise and edges) increases with detection. While pixel spacing improves with decreasing pixel size, edge and noise detection deteriorates. The gaussian matrix's size is x,y, and its middle, which spans the points -x to +x, is located at x = 0 and y = 0.

Feature Extraction

Red, green, and blue are converted to create histogram color, which shows three attributes: true color, color strength, and color brightness. A data image format is used to calculate the feature histogram's scale value. The histogram color space feature extraction was used to extract the mean, standard deviation, variance, and skewness of the urine glucose strip data input values.

Support Vector Machine Model

Support Vector Machine (SVM) algorithm is utilized for a variety of classification and regression issues, such as speech, natural language processing, medical applications, and signal processing. The SVM algorithm's goal is to monitor learning image recognition by identifying a hyper plane that, as much as feasible, distinguishes data points from one class from those from another. The hyper plane with the biggest difference between the two classes is called "best," and it is shown as plus vs minus in the figure.4. The maximum width of the slab parallel to the hyper plane without any internal data points is called the margin. The approach can only locate such a hyper plane for linearly separable problems; for the majority of real-world problems, it maximizes the soft margin while permitting a minimal amount of misclassifications. In essence, an SVM model is a hyper plane in multidimensional space that represents many classes. In order to minimize error, SVM will generate the hyper plane in an iterative method. SVM aims to identify a maximum marginal hyper plane (MMH) by classifying the datasets.

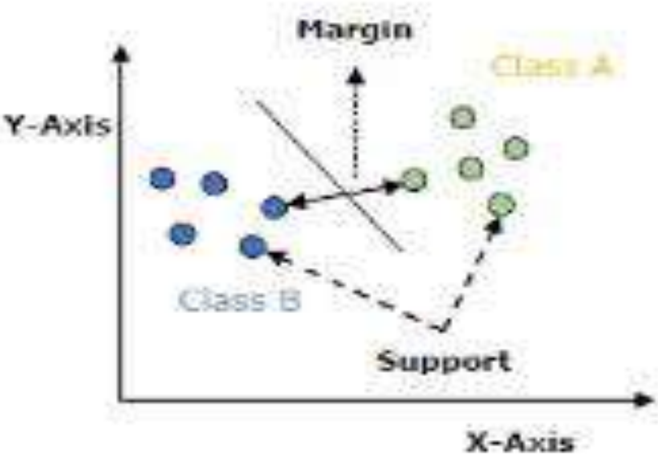

Figure 4: Support Vector Machine Model

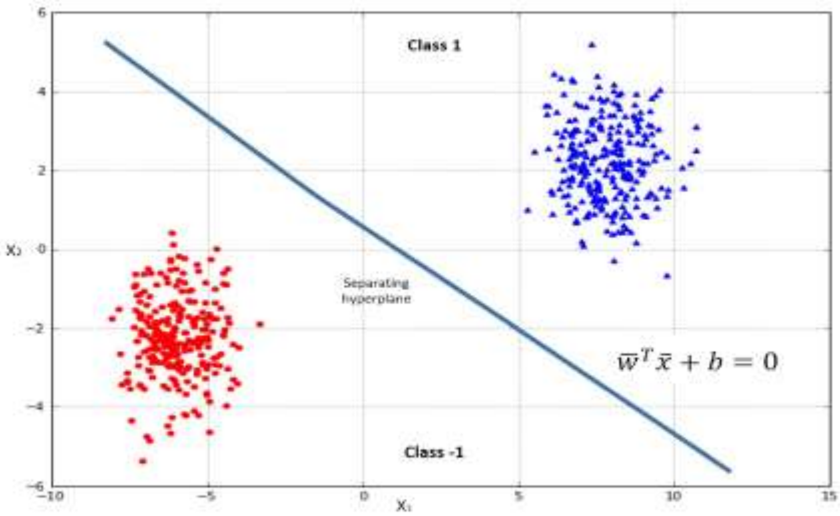

Figure 5: Linear SVM Classification

By determining the ideal straight-line decision boundary that maximizes the margin between two classes, linear SVM classification divides them. The separation hyper plane that separates Class 1 and Class -1 is shown in Figure.5 by the blue line. The data points that are closest to this boundary, known as support vectors, identify it and ensure the maximum distance. This results in an accurate and dependable classification for linearly separable data. By maximizing the margin, linear SVM improves generalization performance on unseen data. Due to its computational efficiency, it finds extensive application in image processing, pattern recognition, and biomedical data classification.

IV RESULTS AND DISCUSSION

The original image utilized for the glucose analysis is shown in Figure 6. A consistent green textured surface with little shade and intensity variations is how the image appears. Its background is smooth and uniform since it lacks any recognizable items or patterns. It may be utilized as a basis input image for image processing or enhancement procedures, based on its visual features.

The filtered image from the glucose content analysis utilizing image processing techniques is shown in Figure 7. The image displays a green surface that has been smoothed out by filtering out noise and slight changes in intensity. The consistent texture shows that important elements have been enhanced while undesirable distortions have been suppressed. The accuracy of future feature extraction and glucose concentration estimation is improved by this preprocessing step.

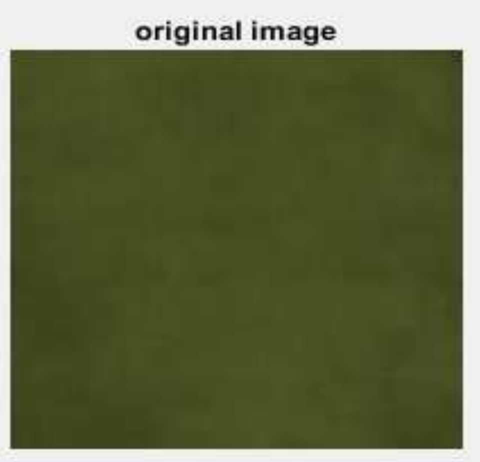

Figure 6: Input Image

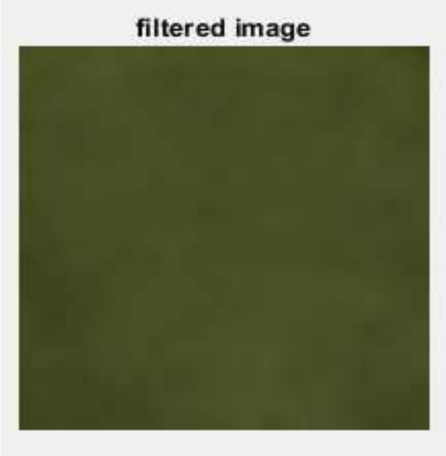

Figure 7: Filter Image

The final classified output of the glucose content analysis system using image processing techniques is shown in Figure 8. The retrieved features and intensity patterns are used to classify the processed image into predetermined glucose level classifications. The categorization result demonstrates how well the feature extraction and filtering techniques worked. The system's capacity to precisely detect and distinguish between different glucose concentration levels is validated by this output.

Figure 8: Classified Output

The confusion matrix for the glucose content analysis system's categorized output is displayed in Figure 9. Good model accuracy is demonstrated by the diagonal elements (9, 6, and 8), which show correctly categorized samples for Classes 1, 2, and 3, respectively. Class 1 and Class 2 are slightly misclassified, as indicated by the off-diagonal values (1 and 2). Overall, the matrix demonstrates that the suggested classification method based on image processing produces accurate and efficient glucose level prediction.

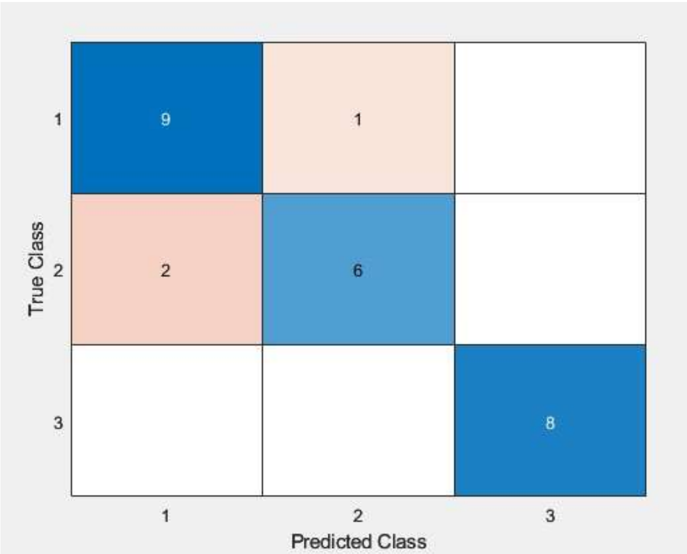

Figure 9: Confusion Matrix

The performance evaluation metrics of the suggested strategy for classifying glucose content are shown in Figure 10. Precision is the highest, followed by F1-score and slightly lower recall, as shown in the bar chart that displays precision, recall, and F1-score values. The findings show that the model produces few false positives while achieving high predicted accuracy. Overall, the performance indicators show how reliable and successful the glucose analysis method based on image processing is.

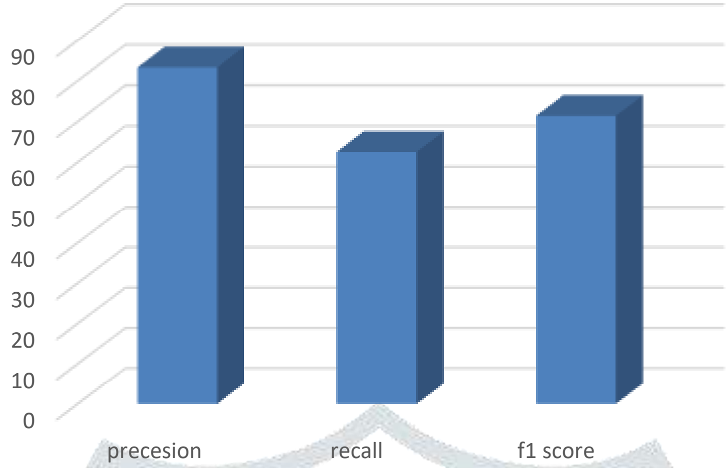

Figure 10: Performance Metrics

V CONCLUSION

This study examines the effectiveness of a non-invasive method for tracking blood sugar levels. When using the histogram, Gaussian filters are especially useful for eliminating image noise and identifying the most important color value. An very successful and promising method for analyzing glucose content is the use of SVM classifiers and image processing algorithms. The goal of this work was to address the need for an effective and non-invasive technique to measure glucose levels, which is essential for the management of metabolic diseases like diabetes. In order to properly extract glucose-related information from photographs, the research used image processing, which eliminated the need for laborious laboratory procedures and traditional blood samples. Based on the processed visual data, the SVM classifier showed that it could reliably predict glucose levels. By using pertinent feature engineering approaches, the model's performance was further improved, enabling predictions that were solid and trustworthy. Using testing data from 3600 databases, the SVM technique is applied to classify patient glucose information. A decent accuracy result of 85% is obtained when classification is done using the Support Vector Machine with a test time of 0.5 seconds. Additionally, while determining diabetes, pre-diabetes, and normal diagnostics, this data will be taken into account. More study will be required to enhance classification using a different picture technique for identification as the field develops and refines.

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