Non-invasive Technique for Detecting Glycosuria Through Image Processing and Deep Learning Approaches

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Abstract. Glycosuria level monitoring is a fundamental aspect of diabetes management, enabling proactive and personalized care to prevent complications, improve overall health, and enhance the quality of life for individuals with diabetes. Conventional glycosuria monitoring methods often involve invasive procedures, potentially risking the immune system, especially with repeated injections. The research focuses on a non-invasive method utilizing urine samples for glycosuria testing to address these concerns. The proposed method integrates image processing techniques, such as Gaussian filtering and image resizing, to optimize input data with machine learning approaches. Deep learning, especially convolutional neural networks is employed for their ability in feature extraction and pattern recognition. The system aims to achieve high accuracy in categorizing glycosuria levels into groups such as diabetes, prediabetes, and normal, providing a reliable and non-invasive alternative to traditional glycosuria monitoring techniques. This approach shows promise in enhancing patient compliance and overall health monitoring for individuals requiring regular glucose assessment. The accuracy of the proposed method based on CNN achieves 98.54% where the existing method based on support vector machine (SVM) achieves only 88.46%. it is evident from simulation results, the proposed method attained 11.39% improved accuracy when compared to existing SVM.

Keywords: Glycosuria · gaussian filter · Convolutional Neural Network · Classification · Deep learning · Accuracy

1 Introduction

Recently, the concept of a smart ecosystem emerged, which focuses on the well-being of the citizens with respect to all aspects like healthcare, transportation, security, etc. [1]. Smart cities facilitate all basic requirements with the aid of technology like the Internet of Things, artificial intelligence, machine learning, etc. [1, 2]. In this context, efficient

P. Pareek et al. (Eds.): IC4S 2024, LNICST 597, pp. 204–214, 2025.
https://doi.org/10.1007/978-3-031-77075-3_17

healthcare is one of the key features of the smart-eco system. In a smart healthcare system, the detection and diagnosis of critical diseases are carried out with the help of machine-learning approaches. The healthcare system become robust, efficient, and effective due to the introduction of machine learning in the healthcare system [3–6].

Nowadays, due to unhealthy lifestyles, various diseases are causing the life threat to citizens. Glycosuria, the presence of glucose in the urine, is a key indicator of abnormal blood glucose levels and is often associated with conditions such as diabetes [7]. Traditional methods for detecting glycosuria involve invasive procedures, including blood tests and needle-based glucose monitoring, which can be uncomfortable, inconvenient, and pose potential risks. As a response to these limitations, there is a growing interest in developing non-invasive techniques that can accurately and efficiently detect glycosuria [8]. The conventional methods for detecting glycosuria often involve blood samples or invasive glucose monitoring, which can be burdensome for patients, leading to reduced compliance and reluctance for regular testing. Our non-invasive approach seeks to address these challenges by utilizing urine samples, a readily available and less intrusive medium for detecting glycosuria [9]. This approach enhances patient comfort and encourages regular testing, promoting proactive health management. The proposed approach incorporates sophisticated image processing techniques, including Gaussian filtering and image resizing, to enhance the quality and relevance of the input data. By optimizing the images of urine samples, we aim to improve the precision of glycosuria detection. This preprocessing step is essential for preparing the data for subsequent machine learning algorithms.

Deep learning, particularly CNNs, is employed for its exceptional feature extraction and pattern recognition capability. CNNs have proven successful in various image analysis tasks, making them ideal for interpreting complex patterns within urine sample images. Machine learning enhances glycosuria detection accuracy and reliability, effectively classifying glucose level categories [10]. Therefore, this work aims to develop a non-invasive technique that can accurately detect glycosuria through the integration of image processing and machine learning approaches. Such a technique holds significant promise for improving patient compliance, reducing the discomfort associated with traditional invasive methods, and offering a reliable tool for continuous monitoring of glucose levels. The outcomes of this work have the potential to revolutionize glycosuria detection, contributing to enhanced healthcare practices and better management of conditions related to abnormal glycosuria levels.

2 Literature Review

Historically, glycosuria has been detected through invasive methods such as blood tests and needle-based glucose monitoring. While these techniques provide accurate results, they are associated with patient discomfort, reluctance for regular testing, and potential risks. The need for non-invasive alternatives has driven the exploration of innovative approaches utilizing image processing and machine learning. Recent studies have explored the use of non-invasive methods for glycosuria detection, focusing on readily available bodily fluids such as urine. Utilizing urine samples eliminates the need for blood draws or painful glycosuria monitoring, significantly improving patient comfort and compliance.

Non-invasive approaches contribute to a more patient-friendly experience, encouraging regular monitoring and early detection of abnormal glycosuria levels. The study in [11], presents the design and simulation of a photonic crystal structure in a silicon slab with 2-D air holes and a line defect. The intended application is the detection of elevated glycosuria concentrations in urine, ranging from 0–15 to 10 gm/dl. The simulation covers the wavelength range of 1530–1565 nm. The authors of [12] has introduced a surface plasmon resonance sensor design utilizing a prism-based structure, incorporating multiple layers of black phosphorous and hexagonal boron nitride for detection of glucose in urine. The proposed work in [13] has introduced and examined an automated diagnostic system that employs a three-layered artificial neural network (ANN) in conjunction with the Pima Indians Diabetes dataset. The research work in [14], has illustrated the utilization of an ANN for classifying diabetes risk, relying on the symptom information of patients. The authors of [15], explores the diverse methods for handling missing values to enhance classification accuracy and investigates the influence of preprocessing on the classification process. In [16], the primary aim of the authors is to examine the meteorological factors influencing the occurrence of hypertension and establish a forecasting model. This study in [17], introduced a novel approach by considering the prediction of fasting blood sugar (FBS) as a strategy for forecasting diabetes and presented a model for predicting FBS based on various factors in the blood test of individuals. In [18], the authors have conducted a comparative analysis of various artificial neural network techniques for the early detection of Diabetes Mellitus. In [19], the authors have proposed a rapid and intelligent system utilizing an ANN for the early detection of diabetes which aims to assist healthcare professionals in timely intervention, thereby halting the progression of the disease.

The literature review covered various aspects of healthcare and medical research focusing on designing a photonic crystal structure, surface plasmon resonance sensor for detecting elevated glucose or urea concentrations in urine [20]. Additionally, it delves the role of ANN in detecting diabetes mellitus under various scenarios. While non-invasive techniques show promise, challenges remain, including the need for large and diverse datasets, standardization of image acquisition protocols, and addressing potential biases [21]. Future research should focus on overcoming these challenges to establish the reliability and generalizability of non-invasive glycosuria detection methods. Hence, this work focused on developing a non-invasive technique for detecting glycosuria based on image processing and CNN.

3 Proposed Model

To address the drawbacks associated with invasive traditional glucose monitoring methods, which involve repeated injections with potential adverse effects on the immune system, this work introduces an innovative approach to glucose content analysis. Employing advanced techniques in image processing and CNNs, this work emphasizes the development of a non-invasive method for glycosuria testing, utilizing readily available urine samples. The proposed method incorporates critical processes such as glycosuria classification through deep learning, leveraging tools like Gaussian filters and image resizing to enhance the quality of the data. By avoiding the discomfort associated with invasive procedures, this approach aims to establish a more patient friendly and accessible means of assessing glycosuria levels.

3.1 Block Diagram

The block diagram for proposed approach for detecting glycosuria has been depicted in Fig. 1. it involves in three phases such as pre-processing, CNN, and classification of samples. CNN represent a pivotal element in the domain of deep learning, bringing about a transformative impact across diverse fields. They have especially revolutionized computer vision, displaying an unmatched capacity to understand and extract complex patterns from visual data. Finally, the proposed method is evaluated for accuracy and compared with SVM approach.

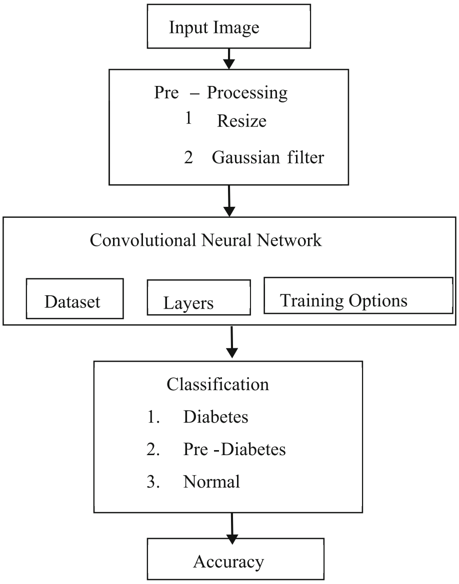


Fig. 1. Block diagram of proposed approach

3.2 Pre-processing

In the realm of glycosuria content analysis pre-processing assumes a pivotal role as a crucial stage in refining raw input data, presented as images containing information derived from urine samples (patch strips). Glycosuria data collection was conducted on patients with diverse glucose level histories, including diabetes, pre-diabetes, and normal levels. Data gathering involved the utilization of urine strips and specialized equipment for glycosuria detection. The study aimed to comprehensively understand glycosuria processing across various groups, facilitating effective management of glucose-related conditions. During this preparatory phase, essential procedures are undertaken, with a primary focus on image resizing to standardize dimensions, ensuring consistency in data input. The image is resized to dimensions of 2 cm by 2 cm to improve user accessibility to a wider range of color selections. PNG format is used for picture creation in this process. It is important to use a Gaussian filter at this stage to reduce noise and improve the clarity of the image. The following equation, Eq. 1, define the characteristics of the Gaussian filter,

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2 + y}{2\sigma^2}} \quad (1)$$

The Gaussian matrix element G (x, y) signifies the standard deviation (σ), positioned at coordinates [x, y]. A larger standard deviation leads to increased spacing between distant or faint pixels, such as edges and noise. Conversely, as the pixel distance decreases, precision improves, and noise detection quality improves.

4 Convolutional Neural Networks

In image analysis and classification tasks, including the detection of glucosuria from urine sample images, Convolutional Neural Networks (CNNs) have appeared as powerful tools. The architecture of a CNN is designed to automatically learn and extract hierarchical features from raw pixel data, enabling effective discrimination between normal and glycosuria samples.

Dataset

The images are organized into folders based on their respective classes (e.g., normal and diabetic). The image Datastore function is used to create an Image Datastore object, which eases efficient loading of images from disk. Once the dataset is loaded, it is split into training and validation sets using the split Each Label function. This function divides the dataset into two subsets based on a specified proportion (e.g., 80% for training and 20% for validation). This ensures that the model is trained on a part of the data while reserving a separate part for evaluating its performance.

Layers

The pre-processed urine sample images are fed into the input layer of the CNN.
This layer serves as the entry point for the image data into the network.
Convolutional Layer
The input images pass through a series of convolutional layers. Each convolutional layer consists of learnable filters or kernels that convolve with the input image to extract hierarchical features. These features include patterns, textures, edges, or shapes relevant to the presence of glucose in the urine sample. The following equation (Eqn.2) defines the characteristics of Convolutional layer.

$$f(\sum\nolimits_{m=0}^{M-1} \sum\nolimits_{n=0}^{N-1} \sum\nolimits_{c=0}^{C-1} W_{m,n,c,k}^{(l)} . I_{i+m,j+nc}^{(l-1)} + b_k^{(l)} \quad (2)$$

$I_{i+mj+n,c}^{(l-1)}$ represents the input to layer l at position $(i + m, j + n)$, $W_{m,n,c,k}^{(l)}$ denotes the weights of the k th filter in a layer l at spatial position (m, n) and channel c. $b_k^{(l)}$ is the bias term associated with the k th filter. $f(.)$ denotes the activation function, typically a rectified linear unit (ReLU) activation.

Pooling Layer

After convolutional layers, pooling layers are used to reduce the spatial dimensions of the feature maps while keeping the most salient features. Max pooling (Eqn.3), for instance, selects the maximum value from each local region of the feature maps, effectively down sampling the data and enhancing computational efficiency.

$$max_{m,n}\left(I^{(l)}_{2i+m,2j+n,k}\right) \tag{3}$$

Fully Connected Layer

The output from the last pooling layer is flattened and passed through one or more fully connected layers. These layers integrate high-level features learned from convolutional and pooling layers to perform classification tasks. Neurons in these layers are connected to all activations in the previous layer, allowing for complex feature combinations and discrimination between normal, prediabetic and diabetic urine samples as expressed in Eq. 4

$$f\left(ReLU\left(W^{(l)}.O^{(l-1)} + b^{(l)}\right)\right) \tag{4}$$

Training Options

The training options used in the convolutional neural network (CNN) for detecting glycosuria encompass several crucial parameters. The stochastic gradient descent with momentum (SGDM) optimization algorithm is chosen as the optimizer, allowing for efficient adjustment of network weights during training. The "Execution Environment" parameter is set to "auto", enabling automatic selection of the hardware accelerator, which enhances computational efficiency. An "Initial Learn Rate" of 0.001 is specified to control the step size of parameter updates, ensuring a balanced approach to learning. The maximum number of epochs is defined as 100, regulating the total number of iterations over the entire dataset during training. A "Minibatch Size" of 25 is set to determine the number of samples processed in each iteration, optimizing memory usage and computational resources. Furthermore, data shuffling is performed "every-epoch" to prevent the network from learning the order of samples and facilitate better generalization.

Validation of the model's performance is conducted using the provided validation dataset, defined by the "Validation Data" parameter, which helps check the network's ability to generalize to unseen data. Validation occurs every 50 iterations, as specified by the "Validation Frequency" parameter, ensuring frequent evaluation of the model's progress. The training process is executed with verbosity enabled, denoted by "Verbose" set to true, providing detailed progress updates during training. Additionally, training progress plots, including training loss and accuracy curves, are displayed with the "Plots" parameter set to "training-progress", aiding in visualizing the model's performance over epochs. Collectively, these training options orchestrate an optimized training regimen for the CNN, guiding the model towards accurate detection of glycosuria from urine sample images. The dataset images have been trained to the CNN model for detecting the classification of image based on urine samples. The training process has been depicted in Fig. 2.

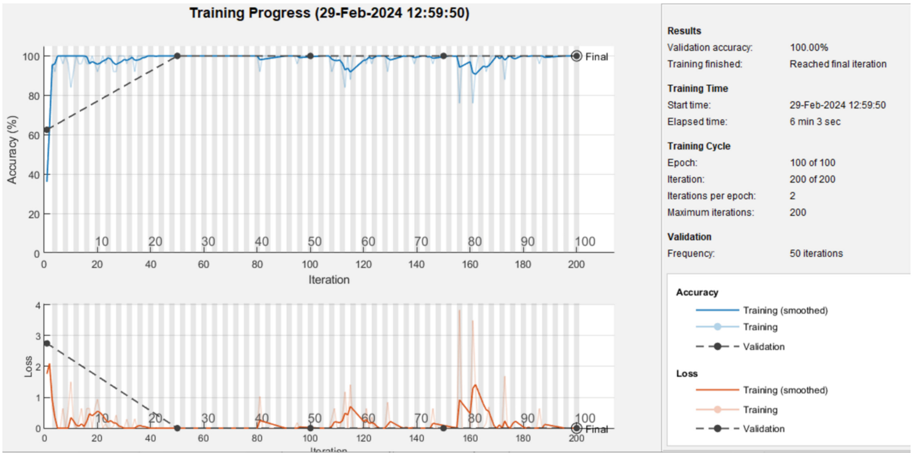


Fig. 2. Training process of data.

4.1 Classification Using CNN

The convolutional neural network (CNN) method employed for categorizing glucose levels operates through a process of training and prediction. Initially, the CNN model is trained using a dataset comprising images of urine glucose strips along with their corresponding labels indicating the glycosuria levels. During training, the network learns to extract hierarchical features from the input images through successive layers of convolutional, batch normalization, and pooling operations. These learned features capture discriminative patterns indicative of varying glycosuria concentrations within the urine samples. The training process involves iteratively adjusting the parameters of the network to minimize the discrepancy between predicted and actual glycosuria levels, guided by a specified loss function. During prediction, the network utilizes the learned feature representations to classify the input images into various categories corresponding to specific glucose levels. This prediction process involves passing the input images through the trained network and obtaining the output predictions, which are probabilities associated with each glucose level category. The dataset samples have been classified into three types based on the threshold levels of urine samples with the normal diabetic ranges. Figure 3 depicts the classification of urine sample into pre-diabetics, diabetics, and normal.

5 Simulation Results

The proposed method has been divided into several stages. The entire glycosuria collection has 525 images (urine patch strips), including 192 for diabetes patients, 160 for pre-diabetic patients, and 1 for regular glucose patients. Frist, the pre-processing stage (see Fig. 4). The input image has been taken from the captured images from the dataset samples (see Fig. 4 (a)), then crop the images and resize with specified dimensions (see Fig. 4(b)). After the resize of original image, applied to median filter for noise removal (see Fig. 4(c)).

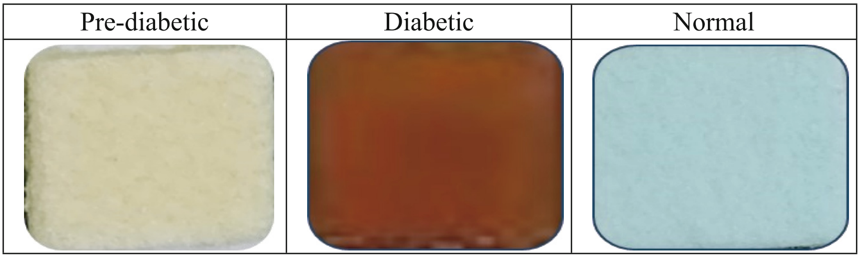


Fig. 3. Clasaification of Urine strip samples.

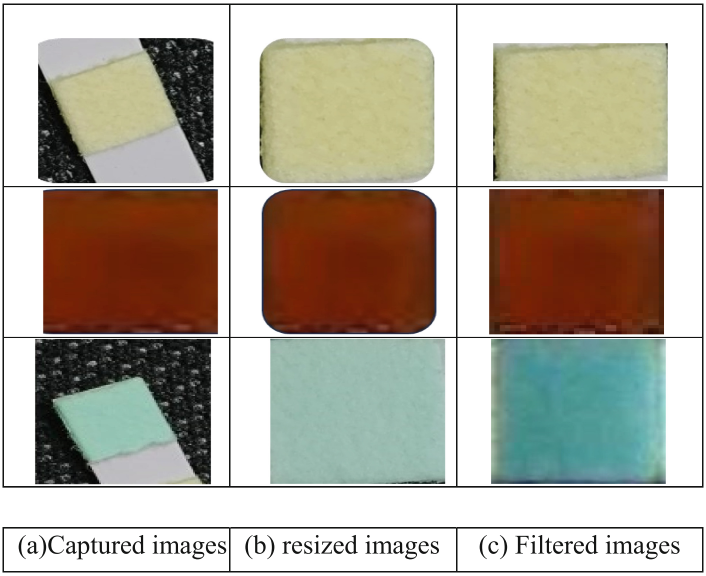


Fig. 4. Image pre-processing.

After the pre-processing, the data samples are classified into three groups based on the threshold values of diabetics. The proposed approach automatically compares the threshold values with taken urine samples for the pre-diabetic, normal, and diabetic conditions. The classification of urine samples has been depicted in Fig. 5.

The accuracy of the proposed method has been evaluated with increasing iterations and number of images as shown in Fig. 6. The accuracy can be evaluated using Eq. 5.

$$\text{Accuracy} = \frac{(TP + TN)}{(TP + TN + FP + FN)} \tag{5}$$

True Positives (TP) represent instances correctly predicted as positive (glycosuria), while True Negatives (TN) denote instances correctly predicted as negative (normal). False Positives (FP) indicate instances incorrectly predicted as positive (glycosuria) when they are actually negative (normal), and False Negatives (FN) signify instances incorrectly predicted as negative (normal) when they are actually positive (glycosuria).

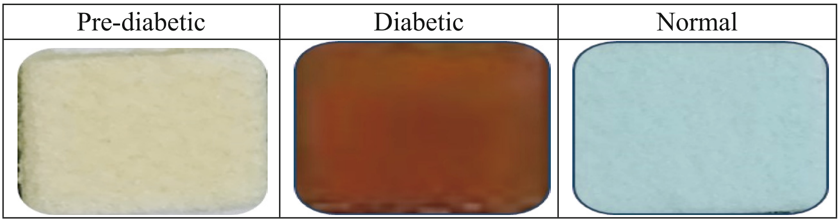
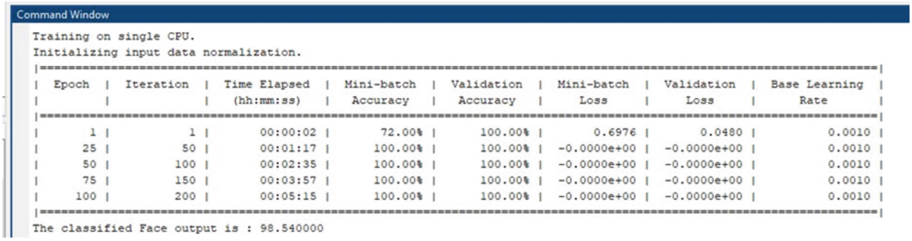


Fig. 5. Classified output of urine samples.

The statistics of accuracy evolution revels that, the proposed approach out reaches the existing SVM model in terms of accuracy. Finally, the performance comparison between proposed method (CNN) and existing method (SVM) with respect to accuracy has been evaluated and shown in Fig. 7. The proposed method based on CNN achieves an accuracy of 98.54 accuracy when compared to the existing method based on SVM.



Command Window

Training on single CPU.
Initializing input data normalization.

Epoch	Iteration	Time Elapsed (hh:mm:ss)	Mini-batch Accuracy	Validation Accuracy	Mini-batch Loss	Validation Loss	Base Learning Rate
1	1	00:00:02	72.00%	100.00%	0.6976	0.0480	0.0010
25	50	00:01:17	100.00%	100.00%	-0.0000e+00	-0.0000e+00	0.0010
50	100	00:02:35	100.00%	100.00%	-0.0000e+00	-0.0000e+00	0.0010
75	150	00:03:57	100.00%	100.00%	-0.0000e+00	-0.0000e+00	0.0010
100	200	00:05:15	100.00%	100.00%	-0.0000e+00	-0.0000e+00	0.0010

The classified Face output is : 98.540000

Fig. 6. Classified accuracy of the CNN model as attained in the output of simulation

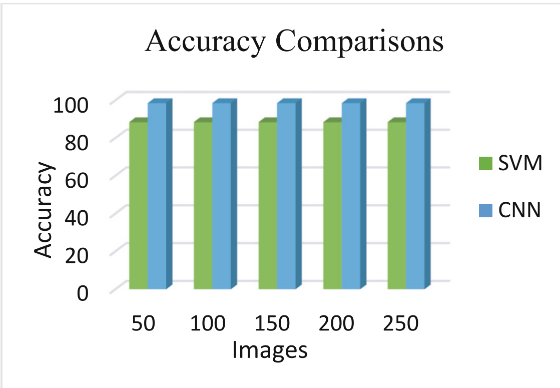


Fig. 7. Performance comparison of achieved accuracy between SVM and proposed CNN.

6 Conclusion

The objective of the proposed work is to attain precise categorization of glucose levels into diabetes, pre-diabetes, and normal groups. This offers a dependable and non-intrusive substitute for conventional glucose monitoring methods. This pioneering approach holds the potential for improving patient adherence and overall health monitoring in individuals needing regular glucose assessments. The accuracy of the proposed CNN-based method reaches 98.54%, outperforming the existing support vector machine (SVM) method, which achieves only 88.46%. Simulation results clearly demonstrate a notable 11.39% enhancement in accuracy with the proposed method compared to the current SVM approach.

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