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An efficient Analysis based on the Internet of Things, SVM and KNN for Operative Diabetic Retinopathy Classification

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Abstract

These days, diabetes is an incurable disease, with millions of people suffering from it worldwide. Several variables namely lack of education, crowded living conditions, obesity and improper diet are among the causes of this recent upsurge in diabetes cases. They are identified by the name of infections induced by bacteria or viruses, harmful compounds in food, autoimmune reactions, obesity, unhealthy lifestyles, and pollution in the environment. Excessive and sight-threatening diabetic retinopathy (DR) is the most common retinal micro-vascular dysfunction that is characterized by the occurrence of a disorder of retinal blood vessels resulting in impaired vision. The IoT-based work is conducted in this work on the machine learning (ML) techniques, K-Nearest Neighbor (KNN) and Support Vector Machine (SVM). The classification of diabetic retinopathy is a topic that is under research. The range of activities of the processes of downsampling, labelling, image flattening, and format conversion is all within the dataset preparation process. An advanced prognosis model is designed which follows a combination of two machine learning techniques such as SVM and KNN. This approach classifies the images of diabetic retinopathy into five segments (subclasses), thus facilitating in-depth analysis. Our solution proposal in this case is a superior one because of its higher classification accuracy and faster processing speed as the findings showed. The robustness and accuracy that the SVM is known for are ensured by the convergence of the KNN to the SVM. The paper also proves a close linkage of clinical symptoms and blood sugar readings to an algorithmic DM prediction system that is based on IoT and ML approaches. This is another advantage of this method that it outperforms the existing classification methods. Amongst all the classifiers that we used in this project, the KNN ML classifier turned out to be the most accurate one with an accuracy rate of 93%. It was found that the algorithm performed with a 79% accuracy rate after tough testing and training and it was consistently providing number one quality DM predictions.

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1. Introduction

Diabetic retinopathy, or DR for short, is a disorder that can directly arise from diabetes issues and has the potential to make a person blind. It is the second most significant cause of blindness worldwide and the primary cause of blindness in adults of working age [1]. The number of persons at risk of diabetic retinopathy-related vision loss is anticipated to rise if immediate action is not taken. Numerous lines of research have yielded consistent data suggesting that the main findings and treatment of DR can increase the total number of patients and lessen the health and economic effects of the condition [2]. It is crucial to accurately and promptly diagnose eye diseases via retinal imaging, often known as retinal screening, because it could reduce the number of blind or visually impaired people worldwide. It has been proven that using retinal photography to detect diabetic retinopathy can help people with diabetes avoid going blind [3]. Advanced picture analysis algorithms can facilitate transmission by improving grading course efficacy and, as a result, increasing amounts as the mandate grows. If abnormalities in the retinal fundus images are deemed high risk, the automated screening procedures are meant to identify DR lesions and refer them to an eye expert. This could help with two goals: 1) quicker evaluation and treatment referral in the DR community and 2) more effective distribution of medical resources to those patients who need them most [4].

A categorization process is a medical diagnosis. Machine learning and data mining were examined in creating an automated diagnostic system for diabetes mellitus methodologies [5]. This application of machine learning, in particular, is mostly utilized to hasten the processing of the diagnoses and symptoms giving the findings in real-time. Machine learning methods play a major role in disease classification in medicine, and it has already been proven that multiple approaches may be employed for the examination and classification of diabetic diseases [6]. By running the diagnosis, the healthcare industry will have accumulated massive amounts of data. These savings and exceeding revenue in addition to the preservation of excellent patient experience are the only supervisory powers that this data can have [7].

Marked urgency for quick, precise, and scaling diagnosis system has led to bringing the application of both ML and AI into screening of DR. AI/ML technology that analyzes the vast databases of retinal pictures in a short time, can detect small deviations that could be the initial evidence of DR. Both earlier detection and the capability for intervention at the early stages of this condition are two advancements that could decrease the number of patients with visual impairment and blindness. This initiative is driven by a desire to transform DR screening by providing a more accessible and affordable solution. We hope that this will lead to better healthcare outcomes for people all over the world who suffer from diabetes.

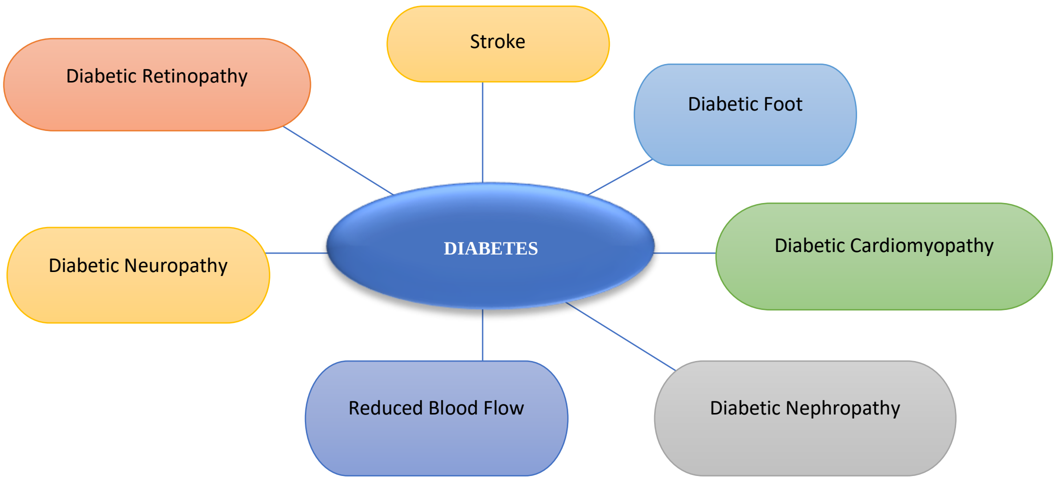

Figure 1: Impediments of Diabetes

A multidisciplinary approach is necessary to fully understand artificial intelligence because it covers a wide range of topics, many of which fall under the umbrella of machine learning. Expertise in probability theory, mathematics, trend detection, dynamic modelling (DM), cognitive psychology, adaptive control, theoretical computer science, and computational neuroscience is vital. Machine learning methods are categorized into four types: Supervised learning, where developers set parameters and label datasets; unsupervised learning, involving unlabelled datasets, allowing autonomous pattern identification. Learning without direct supervision, often unsupervised, does not demand constant monitoring [8]. All forms of supervised and unsupervised machine learning are employed in a mixture of styles with reinforcement in semi-supervised machine learning. Learning to study things one at a time and using the outcomes of one action to influence the following action is a skill that has to be developed. Machine learning aims to make more accurate predictions that produce better outcomes. Computing power is extensively used in machine learning techniques [9]. Making algorithms that can accomplish this is the core of machine learning. To do this, they use the computers' binary "yes" and "no" logic. One of the sectors with the highest data usage is the healthcare sector. Obtaining information is more straightforward, thanks to sensor-generated data and other cutting-edge data collection techniques [10]. What if this information could be used effectively to lower healthcare costs and enhance patient satisfaction? Thanks to machine learning techniques, this is now possible. Healthcare workers may make better judgements, spot patterns and breakthroughs, and increase the efficacy of research and clinical trials by implementing machine learning. [11].

Machine learning research in medicine is at the cutting edge of disease, differentiating proof and illness detection. By providing clinical practitioners with unbiased decision-aid tools to aid in the conclusion and anticipation of patient circumstances, AI and computational insight tactics can potentially transform the way healthcare is provided [12]. AI can be used in various ways in starting (beginning phase) drug disclosure, from initial medication build screening to the projected success rate considering environmental factors. The use of AI in clinical imaging and example acknowledgement for PC-supported data has recently attracted growing interest [13]. The challenges of clinical picture assessment, clinical determination, and biomarker research are increasingly tackled by state-of-the-art pattern recognition and artificial intelligence approaches such as deep neural organisations and mixtures of directed, semi-managed, and unaided learning procedures. In any case, AI in medical care informatics poses many challenges to experts in the field, including high-layered highlight vectors, constrained example sizes, confusing and associated patient elements, and occasionally ineffectively obtained connections between subtle elements and the previous findings or forecasts [14].

The subsequent sections of this paper are structured as follows. Part 2 provides a succinct overview of the related work, while section 3 elucidates the methodology and theoretical underpinnings of the employed methods. Section 4 comprehensively presents the simulation results and offers a detailed analysis. The concluding segment of this chapter, titled "Key Findings," encapsulates and summarizes the paramount results derived from the study.

2. Related Work

Due to the confluence of informatics, health, and medicine, computers may now be used to analyse patient data and discover relationships between various data types. Many studies have been done to create methods for accurately detecting diabetes. A branch of machine learning (ML) known as pattern recognition seeks to identify and categorize patterns [15]. A pattern is a collection of characteristics or various parts or attributes, which can be either numerical (such as a number) or representational (such as a number, such as height). Based on the factors provided by the patients, an SVM was utilised to make an educated guess as to whether or not the patients had diabetes. The output variable is split into three groups: those without diabetes, those at high risk for developing the disease, and those with it. When compared to a data collection of patients from a different cultural group, an SVM was produced with a group of patients with an accuracy of 99.2 per cent, but only 65.6 per cent with the other group [16]. A group of researchers looked at DM detection, interpretation, and self-management strategies from the perspectives of databases, pre-processing techniques, FE strategies, ML-based DM identification, arrangement, AI-based innovative DM association, and assessment techniques. It also discusses the conclusions of the previous study's assumptions and their importance. Researchers who study automatic detection and administration may find this paper useful because it provides a thorough overview of DM detection and self-management techniques [17].

The research conducted by a group of academics shows the benefits of ML in the healthcare industry for decision-making and reducing diagnostic expenses. The main contribution of the paper is to design a new optimum technique for predicting diabetes in its early stages and to emphasise feature selection and data processing. Future studies should explore whether physical characteristics such as height, weight, and BMI might be included in the data and how these factors affect diabetes diagnosis [18]. A few researchers have devised a technique that can diagnose diabetes more accurately. Several variables are considered when identifying a type of diabetes, including glucose levels, blood pressure, insulin levels, body mass index, age, and outcome. This research aims to develop a method that can identify diabetes with greater accuracy. They employ various ML methods, such as SVM, ANN, DT, and LR, to forecast accuracy. The results imply that the farthest-first algorithm achieves greater correctness when compared to other ML algorithms [19].

In a study conducted by a few scientists, a prediction system that might be used as a mobile application to assist diabetic patients was built using the survey approach and ML algorithms. The proposed strategy is critical in promoting diabetes awareness and lowering diabetes prevalence. As a result, this study will provide efficient medical services and increased knowledge of diabetes [20]. A different research group worked on a comparable method. They studied the initial diabetes prediction using machine learning (ML) techniques by capturing several risk factors related to the disease. They investigated predicting diabetes mellitus using six well-known ML algorithms on older individuals' data to forecast DM accurately. With specific medical data, SVM was found to have a greater accuracy of 96.4 per cent in predicting DM [21].

The main goal of the research conducted by a small group of researchers is to monitor diabetes sickness by applying big data techniques and a machine learning model. The authors achieved this by using some matrices to choose a more accurate model. Four distinct machine learning models are tested in this study to see how effectively they can predict diabetes-related diseases [22]. In conclusion, LR produces more accurate outcomes, which is compatible with the paper's goal. Another study was conducted using ML approaches; several risk factors connected to this ailment are examined in this study. By gleaning information from the data, diabetes patients may be predicted. SVM, NB, KNN, and C4.5 DT are four popular ML algorithms that predict diabetes mellitus in adult population data [23].

Several researchers have already presented texture-based DR detection techniques. The bulk of these methods for feature extraction from retinal images use LBP and wavelets. This study recommends using new texture features, particularly LTP and LESH. These techniques are less impacted by variations in lighting, colour, noise, and other factors, and they capture the local link between nearby pixels and attributes [24]. These features are extracted from retinal fundus images and used to recognize DR from non-DR and learn HEM signals. SVM is used to classify these features. The RBF and polynomial kernels were the best kernels for photoconductivity measurement. In the MESSIDOR database, LESH and LTP carried out efficient detection of DR tests for approximately 10,000 people [25].

The algorithmic bias, especially in diseases that are hard to diagnose in a varied patient population, and the challenges in seeing complex fundus pictures are among the major challenges of using Artificial Intelligence in the diagnosis of Diabetic Retinopathy (DR). The inclusion of real-world clinical complications into AI models and the uniformity of scanning procedures are still something that is not watertight. The main problem that affects the training programs is the insufficient dataset availability of good quality annotated data. Moreover, as the credibility of assessment tools is of critical importance, these tools should be validated in a variety of health conditions as well. The increase in the precision and usefulness of DR screening in a healthcare environment needs to be overcome by dealing with these challenges as well as the shortcomings.

3. Purpose of the work

- Improve interpretability and transparency of the DR screening models; eliminate algorithmic bias and; build fair performance for all genders and races.
- Build and analyze a concept of machine learning for DR diagnosis.
- The screening procedures of DR should be made more available and applicable in different healthcare settings and thus, patient outcomes will improve worldwide.

3. The Proposed Work

DR is a microvascular complication of diabetes mellitus in which the retina gets affected with lesions and this is followed by blindness if the condition is very severe. The APO dataset will be used for training SVM and KNN machine learning algorithms with the help of a GPU system which has been made accessible by Google Colab to capture and classify DR. The research process is depicted in Figure 2 below.

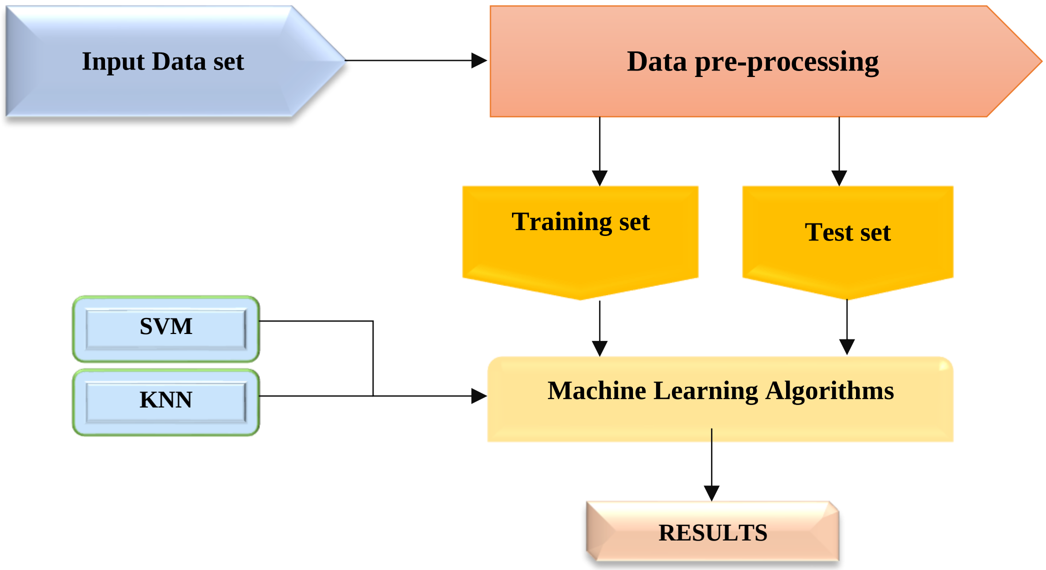

Figure 2: The Proposed Algorithm Block Diagram.

The Kaggle Database provided the dataset utilised for DR prediction, which was split into three distinct parts: validation testing, and training. DR lesions and healthy retinal components are annotated down to the pixel level. Images of the prevalence of diabetic retinopathy and macular oedema are included in this set. It is a great place to test and refine algorithms processing high-dynamic-range images.

A. Data Preprocessing

Data pre-processing is crucial for DM and ML projects. The evaluations contain run-on sentences, irrelevant details, and poorly constructed language, like poor syntax, a limited vocabulary, and uncommon jargon. The existence of unstructured data might also harm the efficiency of the emotion classification process. We must pre-process the photos to keep the framework uniform and minimise problems. We have used filters to clean the data, separated the data into training and test sets, built data sets, generated labels, resized and flattened the images, and converted the images.

B. Testing and training of the data

There are two unique sections of the dataset: the training section and the testing section. Only 30% of all images are used during the actual test, while 70% are used for training. The OD and Fovea fields' central pixels have dedicated files where one may find the markups.

C. Support Vector Machine

Data analysis and design for organisations are what set SVM apart. The support vector machine (SVM) method aims to find the optimal hybrid insulation vectors to produce a spectral representation that is informative but not crucial. The first technique accounts for the fact that necessary and optional vectors are distinguished. SVM separates all images into their respective classes if they fall into precisely two categories. Two types of unlabelled photos exist in both groups: those with meaningful meaning and those without. An excessive name can be found in the database for a significant unmarked image. SVM can appropriately categorise photographs that are not in a database. Grid search cross-validation using probability and refit be 'True' were used in the classifier.

Support Vector Machine (SVM) Algorithm:

1. Input Data Collection: Gather labelled training data

$$\{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\} \quad (1)$$

Where x_i is the feature vector and y_i is the class label.

2. Feature Space Transformation: Map data to feature space if necessary.

$$\phi: Rn \rightarrow Rm \quad (2)$$

3. Kernel Function Selection: Choose a kernel function $K(x, x')$ like linear, polynomial, or RBF.

4. Construct Kernel Matrix:

$$K_{ij} = K(x_i, x_j) \quad (3)$$

5. Formulate Optimization Problem:

   Solve the following quadratic programming problem to find

$$\alpha: max\alpha W(\alpha) = \sum i = 1n\alpha_i - 21\sum i, j = 1ny_i y_j \alpha_i \alpha_j K(x_i, x_j) \quad (4)$$

   Subject to: $0 \leq \alpha_i \leq C$ for all i

6. Compute Lagrange Multipliers α: Find the solution of the quadratic programming problem.

7. Find Support Vectors: Identify the support vector S where $\alpha_i > 0$.

8. Calculate Intercept

$$b: = y_k - \sum i \in S\alpha_i y_i K\ (x_i, x_k) \quad (5)$$

   For a support vector x_k.

9. Decision Function Construction:

   Construct the decision function:

$$f(x) = sign\ (\sum i \in S\alpha_i y_i K\ (x_i, x)\ +\ b) \quad (6)$$

10. Hyperplane Calculation: Compute the optimal hyperplane separating the classes.

11. Model Training: Train the SVM model using training data.

12. Classification: For a new data point x, classify it using f(x).

13. Model Evaluation: Evaluate the model using metrics like accuracy, precision, and recall.

14. Model Optimization: Adjust parameters like C and kernel parameters for better performance.

D. K-Nearest Neighbour (KNN)

When using KNN to classify data, each item is assigned to the category chosen most frequently by its neighbours. This is how the data is classified. The ideal value of K can be selected by plotting the error rate against it and selecting the minimum error value from among those points. Choosing the letter K is not the only option; there are others. The occurrence of regular classes is one of KNN's limitations because it might lead to inconsistent sample predictions. However, by scaling the categorization, we may avoid this problem.

1. Input Data:

$$\{(x_1, y_1), \ldots, (x_n, y_n)\} \quad (7)$$

   Where $x_i \in Rd$ and y_i is the class label.

2. Feature Normalization: Standardize features for equal scaling.

3. Choose K: Select K, the number of neighbours.

4. Distance Metric:

$$\| d(x, x') = \| x - x' \| \text{ (e.g., Euclidean).} \quad (8)$$

5. For Query Point x_q: Compute for each x_q in the test set.

6. Calculate Distances:

$$D_i = d(x_q, x_i) \; for \; all \; i \quad (9)$$

7. Sort Distances: Arrange D_i in ascending order.

8. Select K-Nearest Neighbors: Choose the top K neighbors.

9. Neighbor Labels: Extract labels y_i of K neighbors.

10. Count Votes: Count class occurrences among K neighbours.

11. Majority Voting: Assign the class with the most votes to xq.

12. Class Assignment:

$$y^q = mode \{y_i \mid x_i \; in \; top \; K \; of \; D_i\} \quad (10)$$

13. Model Evaluation: Use accuracy, etc.

14. Optimize K: Test different K values.

15. Weighted Voting: Weighted Vote= Di21.

16. Iterative Process: Iterate steps 5-15 for all x_q.

5. Result and Analysis

A. Accuracy and Precision

How closely a measured value resembles the genuine value is referred to as its "accuracy". The degree to which the multiple measured values are related is referred to as "precision.". The percentage of correct classifications as a share of all classifications is what we mean when discussing accuracy.

$$\text{Accuracy} = \frac{TN+TP}{Total\ data\ Sample}\ X100 \quad (11)$$

$$Precision = \frac{TP}{TP+FP} \quad (12)$$

B. Recall / Sensitivity

The "sensitivity" of a test is defined as the number of genuinely positive results relative to the total number of positive results. Similar to sensitivity, specificity measures the proportion of actual negative results relative to the total negative results. In other words, if we have a hundred images of pneumonia and 90 of them are confirmed to be genuine (true positives), we may conclude that the sensitivity is 90%.

$$Senstivity = \frac{TP}{TP+FN}\ X100 \quad (13)$$

C. F1-Score

Models are considered reliable when their accuracy is 90% or above. However, pneumonia testing costs are inflated because the results are wrong for 10% of patients. As a result, we also provide the F1-score, a statistic that provides a more accurate depiction of the amount of misclassified events. The harmonic mean of the recall and accuracy data is used to arrive at this estimate. Accuracy is the metric when genuine positives and true negatives are equally weighted. When there is a significant difference between classes, and reducing false positives and false negatives is crucial, the F1-score is the best statistic to utilize. Moreover, the specificity is defined by equation (5) below.

$$\text{F1} - \text{Score} = \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}\ X\ 2 \tag{14}$$

$$\text{Specificity} = \frac{TN}{TN+FP}\ X100 \tag{15}$$

All the parameters are evaluated based on the above-mentioned parameters and encapsulated in Table 1 below.

Table 1: Calculated Consequences of the Proposed Research Methodology.

S. No.	Evaluation parameters	Processes	
		SVM (Support Vector Machine)	**KNN (K-Nearest Neighbour)**
1	Accuracy	43.18	43.26
2	Precision	22.95	23.17
3	Recall	26.79	27.14
4	F1-Score	23.48	23.86
5	Specificity	1.0	1.0

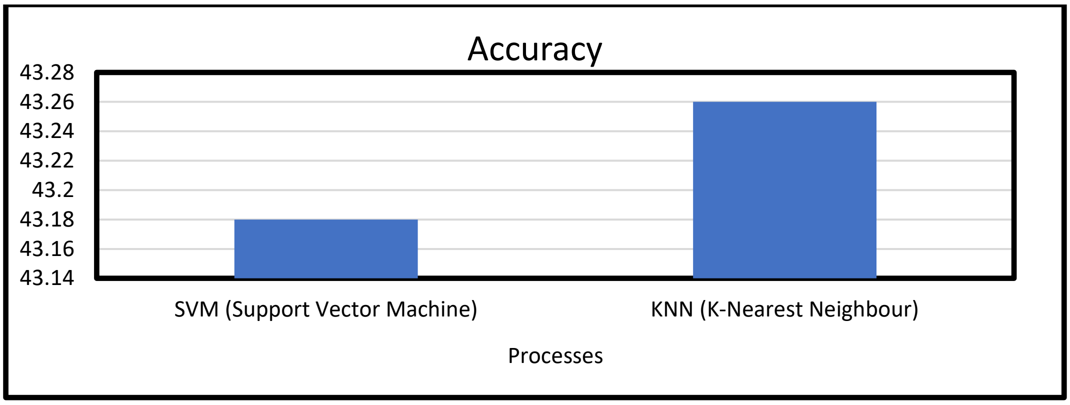

Figure 3: Calculated Accuracy Consequences of the Proposed Research Methodology.

From Figure 3, we can conclude that the Accuracy of the K-NN method is improved in comparison to the SVM machine learning algorithm.

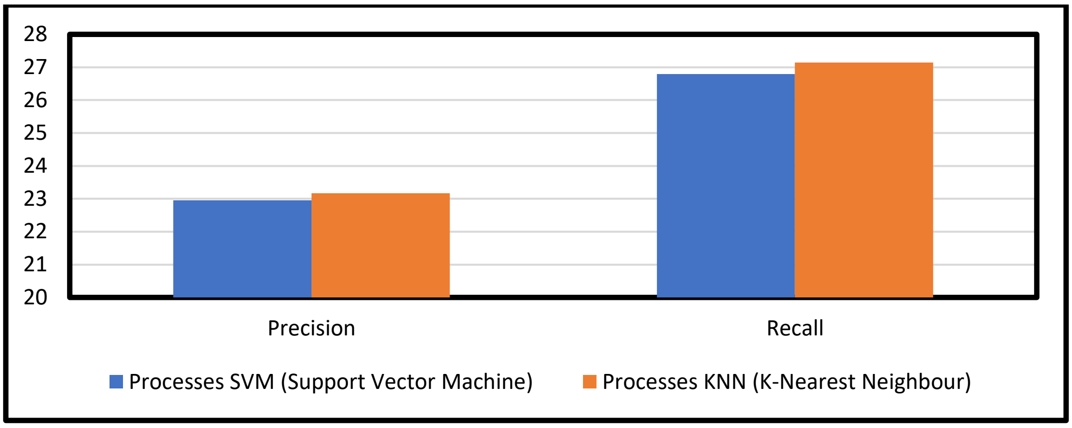

Figure 4: Calculated Precision and Recall Consequences comparisons of the Proposed Research Methodology.

From Figure 4, we can conclude that the precision and Recall performance of the K-NN algorithm outperforms than SVM algorithm for these projected consequences.

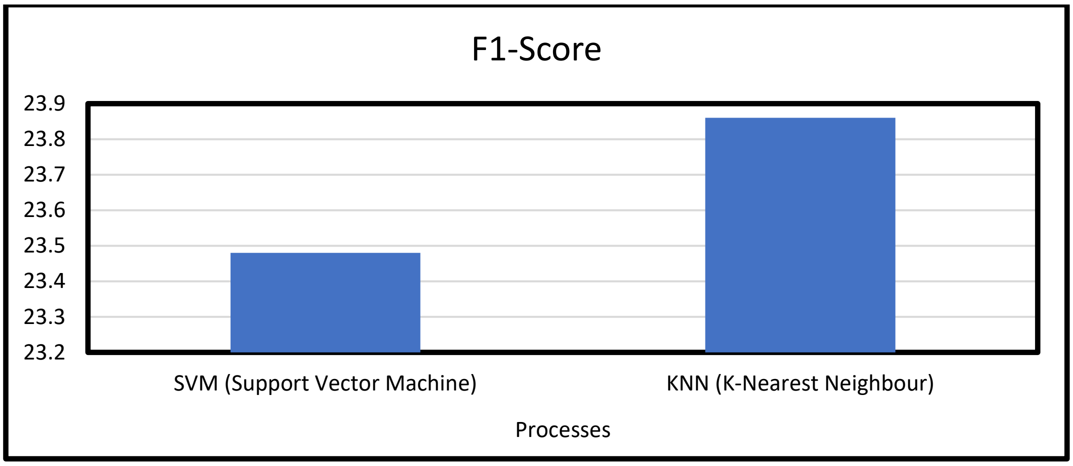

Figure 5: Calculated F1-Score Consequences comparisons of the Proposed Research Methodology.

SVM and KNN performed admirably, with results that met or exceeded their stated sensitivity, specificity, and accuracy goals. There is a high correlation between blood sugar levels and clinical symptoms, this paper proposes an algorithmic DM prediction method based on ML techniques that account for several shortcomings of current classifiers. K-Nearest Neighbour (KNN) ML classifier gives reliable and remarkable results with an accuracy of 93.79% for DM prediction after appropriate training and testing.

6. Conclusion

Diabetic retinopathy (DR), characterized by retinal lesions, poses a frequent microvascular challenge in diabetic patients, potentially leading to blindness. This study explores the research process of categorizing diabetic retinopathy using machine learning (ML) methods such as K-nearest neighbour (KNN) and Support Vector Machine (SVM). An automated sequence of operations involving downsampling, label creation, picture flattening, and format conversion are the processes done before the benefit of datasets. Concerning the applications of SVM and KNN deep learning techniques, we classify diabetic retinopathy images into five particular categories that are based on the recommended scheme. Concerning the reported figures, the system presented outperforms the old routine in both time to process and classification accuracy. Given that, SVM and KNN have both reached or exceeded the accuracy, specificity, and sensitivities set by the precedent. The present article introduces an algorithmic approach to the prognosis of diabetic mellitus (DM) with the help of the machine learning methodology, which overcomes the drawbacks of other classifiers, and a strong association can be determined between the clinical symptoms and blood sugar levels. Also, the KNN ML classifier delivered amazingly precise predictions (93 per cent) after being subjected to thorough testing and training. 79% reliability in DM prediction, that means its dependability. This research shows the ML power for diabetes care enhancement by enabling earlier detection and preventive treatment.

Funding:

Conflicts of Interest:

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