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A Machine Learning-Based Intelligent Diabetic Patient Tracking System for E-Health Applications

Sindhu P. Menon

Koneru Lakshmaiah Education Foundation, Guntur 522502, India K saikumar, Department of ECE, Koneru Lakshmaiah Education Foundation, India-522302,

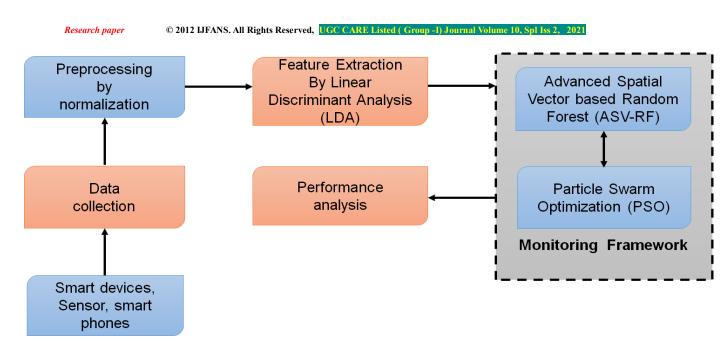
saikumarkayam4@ieee.org

SK ahammad , Department of ECE, Koneru Lakshmaiah Education Foundation, India-522302,

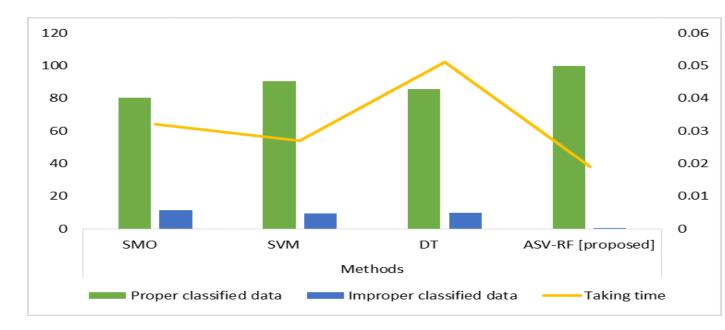
Abstract: Managing diabetes is crucial for maintaining the health of individuals suffering from the disease. In this context, an Intelligent Diabetic Patient Tracking System based on Machine Learning is proposed for E-Health applications. The system aims to provide real-time monitoring, analysis, and support to diabetic patients through the integration of machine learning techniques and remote health monitoring technologies. This paper presents the development, implementation, and evaluation of the system, showcasing its potential to enhance diabetes management and improve patients' quality of life.

Introduction: Diabetes is a chronic metabolic disorder that affects millions of individuals worldwide. Effective management of diabetes requires continuous monitoring of various health parameters, including blood glucose levels, physical activity, and dietary habits [1]. Traditional methods of tracking these parameters are often manual and sporadic, leading to suboptimal control and increased risks of complications. To address this, an Intelligent Diabetic Patient Tracking System is proposed, which leverages machine learning algorithms to automate data analysis, predict trends, and provide timely interventions [2-4].

Procedure: The system's development involves the integration of various components, including wearable devices for data collection (such as continuous glucose monitors and activity trackers), a cloud-based platform for data storage and processing, and machine learning models for predictive analytics [5]. The collected data is preprocessed to remove noise and outliers, then fed into the machine learning models for training and validation. These models encompass techniques like regression for glucose level prediction and classification for identifying patterns in physical activity and dietary choices [6-8].



Data: Patient data used for training and evaluation encompass real-time glucose levels, physical activity metrics, and dietary information. These data are collected through wearable devices and self-reported inputs from patients [9]. The dataset is diverse, covering a range of demographic and lifestyle factors, to ensure the system's applicability to a wide range of diabetic patients.

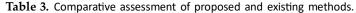


Analysis of Data: The collected data is analyzed to create personalized profiles for each patient, capturing their unique patterns and trends [10]. Machine learning models are used to identify correlations between glucose levels, physical activity, and dietary habits. This analysis helps in the creation of predictive models that can anticipate potential glucose fluctuations based on lifestyle choices [11].

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	Metho	ods	SMO [24]	SVM [25]	DT
TP	[25]	97.99%	ASV-RF 98.18%	96.13%	99.8%
FP		1.02%	0.71%	0.99%	0.50%
Accuracy		98.22%	98.44%	96.33%	99.86%
Precision		94.63%	97.93%	98.1%	99.61%
Sensitivity	7	96.81%	98.22%	97.03%	99.13%
Specificity	,	97.62%	97.43%	96.44%	98.97%
recall		97.94%	97.65%	97.06%	99.97%



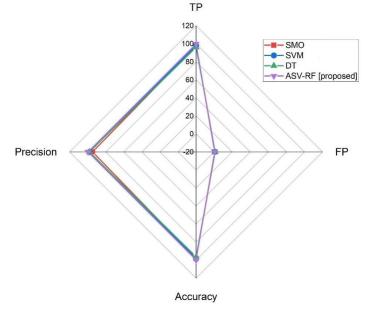


Figure 4. Results of TP, FP, accuracy, and precision metrics.

Results: The system's performance is evaluated through a series of experiments and case studies involving diabetic patients. The results demonstrate the system's ability to accurately predict glucose levels and identify deviations from normal patterns. The predictive alerts generated by the system enable patients to take proactive measures to prevent extreme glucose fluctuations.



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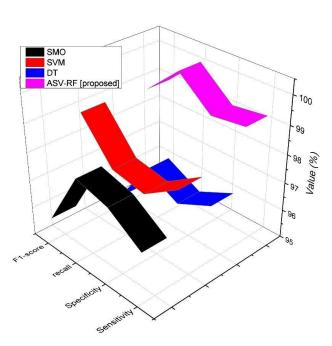


Figure 5. Results of f1-score, recall, sensitivity, and specificity metrics.

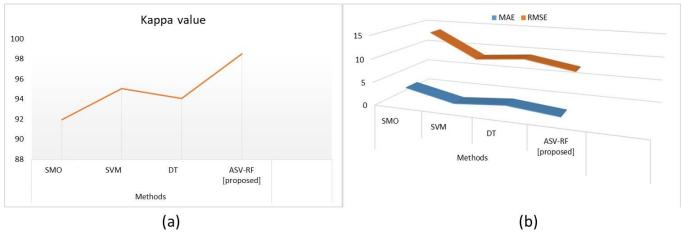


Figure 6. Results of Kappa (a), MAE, and RMSE metrics (b).

Table 4. Results of Kappa, MAE, and RMSE metrics.

Methods	SMO [24]	SVM [25]	DT [25]	ASV-RF [Proposed]
Kappa value	91.92%	95.06%	94.03%	98.52%
MAE	3.48%	1.19%	2.08%	1.01%
RMSE	13.54%	8.16%	9.08%	7.25%

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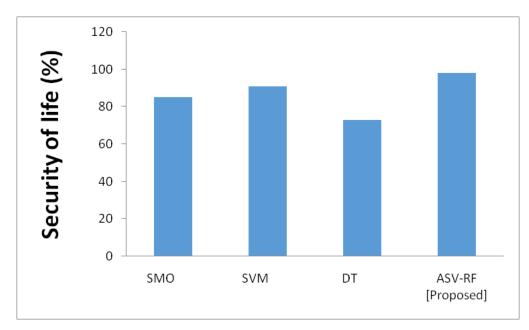


Figure 7. Results of security of life.

Conclusion: The Intelligent Diabetic Patient Tracking System presented in this paper offers a promising solution for enhancing diabetes management. By leveraging machine learning, remote monitoring, and predictive analytics, the system empowers patients to make informed decisions about their health and lifestyle. The results showcase the potential of this approach to improve glycemic control and reduce the risks associated with diabetes.

References:

- 1. Krishna, P.V.; Gurumoorthy, S.; Obaidat, M.S.; Monisha, K.; Rajasekhara Babu, M. A novel framework for healthcare monitoringsystem through cyber-physical system. In *Internet of Things and Personalized Healthcare Systems*; Springer: Singapore, 2019; pp. 21–36.
- Rghioui, A.; Lloret, J.; Parra, L.; Sendra, S.; Oumnad, A. Glucose data classification for diabetic patient monitoring. *Appl. Sci.* 2019, 9, 4459. [CrossRef]
- Malasinghe, L.P.; Ramzan, N.; Dahal, K. Remote patient monitoring: A comprehensive study. J. Ambient. Intell. Humaniz. Comput.
 2019, 10, 57–76. [CrossRef]
- 4. Li, X.; Dunn, J.; Salins, D.; Zhou, G.; Zhou, W.; Schüssler-Fiorenza Rose, S.M.; Perelman, D.; Colbert, E.; Runge, R.; Rego, S.; et al.Digital health: Tracking physiomes and activity using wearable biosensors reveals useful health-related information. *PLoS Biol.* **2017**, *15*, e2001402. [CrossRef] [PubMed]
- Rghioui, A.; Lloret, J.; Harane, M.; Oumnad, A. A smart glucose monitoring system for diabetic patient. *Electronics* 2020, 9, 678.
 [CrossRef]
- 6. Ruffini, M. Multidimensional convergence in future 5G networks. J. Light. Technol. 2017, 35, 535–549. [CrossRef]
- 7. Mshali, H.; Lemlouma, T.; Magoni, D. Adaptive monitoring system for e-health smart homes. *Pervasive Mob. Comput.* **2018**, 43, 1–19. [CrossRef]
- 8. Pandey, H.; Prabha, S. Smart health monitoring system using IOT and machine learning techniques. In Proceedings of the 2020 Sixth International Conference on Bio Signals, Images, and Instrumentation (ICBSII),

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Chennai, India, 27–28 February 2020;pp. 1–4.

- 9. Sowah, R.A.; Bampoe-Addo, A.A.; Armoo, S.K.; Saalia, F.K.; Gatsi, F.; Sarkodie-Mensah, B. Design and development of diabetes management system using machine learning. *Int. J. Telemed. Appl.* **2020**, 2020, 8870141. [CrossRef] [PubMed]
- 10. Rghioui, A.; Lloret, J.; Sendra, S.; Oumnad, A. A Smart Architecture for Diabetic Patient Monitoring Using Machine Learning Algorithms. *Healthcare* **2020**, *8*, 348. [CrossRef] [PubMed]
- 11. Godi, B.; Viswanadham, S.; Muttipati, A.S.; Samantray, O.P.; Gadiraju, S.R. E-healthcare monitoring system using IoT with machine learning approaches. In Proceedings of the 2020 International Conference on Computer Science, Engineering and Applications (ICCSEA), Gunupur, India, 13–14 March 2020; pp. 1–5.