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Sentiment Analysis Utilizing Artificial Intelligence for Effective Health Crisis Management in Diabetics with Smart Urban Environments

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Abstract

Managing diabetic health crises in smart urban environments is challenging due to rapidly changing patient conditions and the need for timely interventions. This study introduces a novel AI-driven sentiment analysis system that integrates social media, IoT sensor data, and electronic health records to detect early signs of distress and health deterioration. By leveraging an Adaptive Median Filtering Technique (AMFT) for preprocessing and Recurrent Neural Networks (RNN) for modelling, the system provides actionable insights from large-scale, heterogeneous data. Experimental results demonstrate that the proposed RNN-AMFT model significantly outperforms baseline methods, achieving 0.92 accuracy, 0.90 precision, 0.93 recall, and a 0.915 F1-score, compared to a baseline CNN (accuracy 0.86, F1-score 0.845). Analysis of 10,000 posts revealed 47% positive, 31% neutral, and 22% negative sentiments, highlighting the system's capability to capture meaningful health patterns. These findings illustrate the potential for real-time monitoring, proactive intervention, and improved diabetic care outcomes. The study establishes a foundation for integrating AI-driven sentiment analysis into clinical workflows, enabling personalized healthcare and scalable health crisis management.

Keywords: *Sentiment Analysis, Diabetics, Adaptive Median Filtering, AI-driven optimization, Smart Urban Environments, Crisis Management*

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I. INTRODUCTION

Diabetics is a chronic metabolic disorder affecting millions of people worldwide, representing a major public health challenge that requires continuous monitoring and timely interventions to prevent severe complications such as cardiovascular diseases, neuropathy, and kidney failure [1-2]. Effective management of diabetics involves not only tracking physiological parameters like blood glucose levels but also understanding patients' behavioural and emotional states, which can significantly influence disease progression and treatment adherence [3-5]. In smart urban environments, the management of diabetic health crises becomes particularly complex due to high population density, environmental stressors, lifestyle dynamics, and limited immediate access to healthcare facilities [6-7]. Urban dwellers often face irregular schedules, dietary inconsistencies, and heightened stress levels, all of which can exacerbate glycemic fluctuations and increase the risk of sudden health crises. Traditional healthcare systems, which primarily rely on periodic clinic visits, self-reported logs, and manual assessments, are inadequate for capturing real-time physiological and psychological signals [8]. Investigating the impact of healthcare access barriers such as affordability, social determinants of health, and cultural competence, on the management of diabetics in urban environments, and how AI-driven sentiment analysis can be leveraged to support early crisis detection and intervention [9]. These conventional approaches often fail to provide early warning mechanisms, leaving critical gaps in proactive intervention and preventive care [10]. Furthermore, patients' emotional states, social behaviours, and sentiment-related cues, which can indicate early signs of distress

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or health deterioration, are largely overlooked in routine monitoring frameworks [11].

To address these challenges, this study introduces a novel Artificial Intelligence (AI)-driven sentiment analysis system designed to monitor and predict health crises in diabetic patients within smart urban settings [12-13]. The proposed system integrates heterogeneous, multisource data from social media platforms, IoT-enabled wearable sensors, and Electronic Health Records (EHRs), providing a comprehensive and real-time view of patients' physical and emotional well-being [14-15]. The system utilizes an Adaptive Median Filtering Technique (AMFT) to preprocess textual data, effectively reducing noise such as irrelevant information, spam, or inconsistent entries, thereby improving the quality of inputs for sentiment analysis [16-17]. Temporal dependencies and sequential patterns in patient-related data are captured using Recurrent Neural Networks (RNNs), enabling the model to detect subtle shifts in sentiment or physiological signals over time [18-20]. AI-driven hyperparameter optimization (AIDO) is employed to automatically fine-tune model parameters, ensuring robust performance, generalization across diverse datasets, and scalability for larger deployments [21-22].

The novelty of this study lies in its holistic approach, combining multisource real-time monitoring, advanced preprocessing, and temporal modelling to deliver predictive, actionable insights [23-24]. By linking emotional and behavioural signals with clinical and sensor data, the system enhances early detection of health deterioration, allowing for proactive interventions that are both timely and personalized [25]. Unlike conventional methods that treat physiological and emotional signals separately, this approach integrates multiple data streams to generate a more accurate and context-aware understanding of patient health [26-27].

The primary objectives of this research are to develop a real-time sentiment analysis framework capable of handling heterogeneous data sources, evaluate its effectiveness in identifying early signs of distress, and demonstrate its potential to improve patient outcomes [28]. Ultimately, the study aims to establish a foundation for scalable, AI-driven health monitoring solutions in urban environments, enabling healthcare providers to deliver timely support, optimize interventions, and empower diabetic patients to better manage their condition within the context of their daily lives. The order of the remaining sections is as follows: Section 2 includes the literature review, Section 3 presents the proposed technique, Sections 4 and 5 examine the results with discussion, and Section 5 describes the paper's conclusion.

II. LITERATURE SURVEY

The literature survey for sentiment analysis utilizing artificial intelligence in effective health crisis management for diabetics within smart urban environments explores the intersection of advanced AI techniques and healthcare analytics. Naveed et al [29] investigate the possible effect of diabetics on the emotional sentiment of patients through sentiment analysis of online forum posts. Analysis of 215 forum posts suggests that diabetics may influence patients' emotional states, as reflected in their shared experiences, issues, and suggestions. Further detailed research is needed to clarify the nature and extent of this relationship.

Ghosh et al [30] developed a system for sentiment analysis, which uses facial expressions in an intelligent healthcare system to identify discomfort, integrating cutting-edge techniques. The proposed system employs a four-component approach involving face detection, feature extraction, pain intensity prediction, and score fusion. Benchmark database experimentation shows better performance than current facial pain expression analysis techniques. Madan et al [31] used machine learning to analyse patient emotions regarding healthcare facilities, concentrating on polarity extraction from patient evaluations to evaluate factors like cleanliness, doctor availability, and doctor-patient interaction. The study successfully implements Python-based sentiment analysis to derive polarity scores from patient feedback, facilitating the calculation of goodness scores for healthcare facilities. This approach aids patients in making informed choices based on aggregated experiences.

Young et al [32] introduced Entity Relationship Sentiment Analysis (ERSA) for understanding the sentiment of entity pairs in biomedical texts, particularly focusing on relationships between biomedical and food concepts. To improve ERSA performance without a substantial quantity of tagged data, CERM, a semi-supervised architecture, is proposed. CERM effectively addresses the ERSA task by leveraging both labelled and unlabeled data, showcasing robust performance in capturing sentiment nuances within biomedical and food-related entity relationships. The approach demonstrates versatility across varied learning scenarios, highlighting its potential for enhancing food-health relationship studies using biomedical text analysis. Kaveripakam et al [33] examined different machine learning algorithms (MLAs) for identifying diabetic diseases by utilizing the PIMA Indian diabetic dataset. Cross-validation using ACR, PCN, RCL, FSC, ROC and K-fold are around metrics used to measure the efficiency of algorithms like SVM, DT, LGR, GDBM, KNN, XGBM, and RF in early diabetics prediction. Among the MLAs tested, Random Forest (RF) demonstrated superior performance in diabetic identification, as evidenced by higher scores across key metrics in test case 4 (70%-30% split). RF outperformed other algorithms, showcasing its potential for effective disease prediction in clinical applications.

Huang et al [34] identified an uncommon instance of concurrent diabetics mellitus with hyperthyroidism and diabetic ketoacidosis (DKA/TS) in a young child, highlighting the necessity of prompt, team-based treatment options and diagnostic and management problems. The case highlights the essential of increased clinical awareness and interdisciplinary teamwork in the efficient management of such complicated endocrine-metabolic illnesses, in addition to the intricacy and diagnostic hurdles presented by the simultaneous incidence of DKA and TS.

Lahsen et al [35] carried out an educational diagnosis in children and teenagers with Type 1 Diabetics Mellitus (T1DM) to determine their educational needs for effective Therapeutic Patient Education (TPE) from diagnosis onwards. Thematic analysis of qualitative interviews identified five key educational themes: understanding the risks connected to type 1 diabetics, keeping an eye on the condition and managing treatments, handling crises, managing food and exercise, and adjusting daily activities to treatment limitations. Integration of TPE is crucial in enhancing skills and managing T1DM effectively among young patients.

Lee et al [36] explored Poland's primary response to a Ukrainian refugee crisis, assessing the humanitarian challenges and evolving priorities, from basic needs to mental health and disease management, emphasizing a collaborative, multi-sectoral approach. The crisis highlighted the necessity for comprehensive needs assessments, robust health surveillance, and culturally sensitive, coordinated efforts across sectors to effectively support and integrate Ukrainian refugees in Poland. Bountouvis et al [37] assessed the status of diabetics management among refugee populations in Lesvos, Greece, including hyperglycaemia levels, cardiovascular comorbidities, treatment availability, and follow-up challenges, aiming to highlight barriers to healthcare access and proposed enhanced management strategies. Among refugee patients with diabetics (81% type 2), findings revealed inadequate treatment continuity, suboptimal glycaemic control (median HbA1c 8.7%), underutilization of insulin (21%), and low adherence to hypertension and lipid-lowering medications. A considerable proportion of patients (42%) were not followed up, underscoring critical gaps in healthcare delivery and the necessity of enhancing global cooperation and support.

Park et al [38] explored barriers to managing diabetics among older Hmong Americans with minimal English proficiency, using qualitative interviews with case managers, family caregivers, and clinicians. Themes include cultural adherence, health inequities, and challenges in navigating Western healthcare systems, highlighting the need for culturally sensitive interventions. Directed content analysis identified cultural adherence, health inequities, and difficulties in managing diabetics as major themes. Subthemes included using shamans and herbs from the Hmong people, mistrust of Western medicine, language barriers, and low health literacy. Addressing these barriers is vital for enhancing diabetics management and healthcare outcomes among older Hmong patients.

III. Research Proposed Methodology

The sentimentality analysis system is driven by artificial intelligence for handling health emergencies in diabetic patients in smooth city settings. This organization will monitor and forecast health issues and provide suitable involvement by leveraging real-time information from wearables, social media, fitness forums and Electronic Health Records (EHR). The methodology entails gathering information from these sources and making it while taking ethical problems like informed consent and data protection into account. To ensure balanced sentiment class representation, the model will be skilled in using labelled datasets. A seamless combination of Internet of Things devices with EHR systems and aware systems for healthcare practitioners will enable real-time information handling in smart urban environments. Stages for assembly and preparing data, model creation, system incorporation, pilot study deployment, analysis, and reporting are all included in the implementation strategy. This strategy makes use of Sentiment examination and artificial intelligence to improve diabetic health crisis management. By making timely interventions, it may also improve patient outcomes and the quality of life.

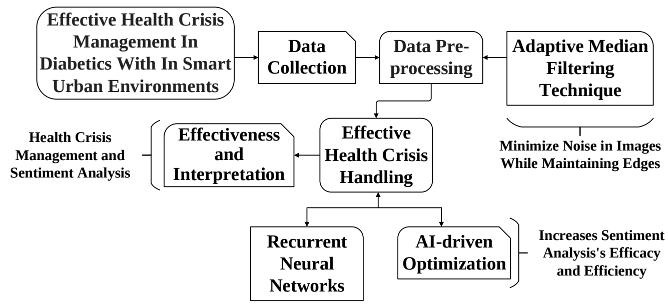


Fig. 1. Block Diagram of the Proposed Work

Figure 1 illustrates a multi-step approach to diabetic health crisis management, combining clinical records, social media, and IoT sensor data with AI-driven sentiment analysis and optimization techniques like RNN and AIDO. This integration enhances prediction accuracy and intervention effectiveness by ensuring the data is accurate and relevant for analysis. RNNs are particularly effective in interpreting sequential data, identifying temporal relationships, and enabling precise monitoring of health issues. The use of AI-driven sentiment analysis with IoT data, such as from wearable devices or continuous glucose monitors (CGMs), facilitates real-time health monitoring. This proactive, data-driven system allows healthcare professionals to detect and intervene in potential diabetic crises, such as hypoglycemia or hyperglycemia, before they escalate, thus improving overall crisis management.

A. Data Collection

Initially, the Nationwide Organization of Diabetics Mellitus and Intestinal and Kidney Infections produced a noteworthy, high-quality data collection, which made up the diabetics mellitus dataset this study employed, which was obtained from Kaggle. Predicting if a human has diabetics using diagnostic parameters is the main goal of consuming this dataset collection. Cases were selected according to strict criteria from a broader database, guaranteeing that all patients were Pima Indian women who had reached the age of 21. Pregnancies, plasma pressure, skin depth, glucose stages, and insulin stages are some of the key elements in this dataset. Sentiment analysis utilizing artificial intelligence for effective health crisis management in diabetics within smart urban environments hinges on the meticulous process of data collection. By gathering comprehensive data on patient sentiments and behaviours, Sentiment analysis powered by AI can provide crucial details about the mental and emotional conditions of diabetic patients. This data, obtained from resources like social media, patient forums, and health apps, enables the identification of early signs of distress and potential health crises. Consequently, real-time monitoring and predictive analytics can facilitate timely interventions, personalized health advice, and enhanced support systems, ultimately improving the overall management of diabetics in smart urban settings. Robust data collection is thus crucial for harnessing AI to optimize health outcomes and crisis management for diabetic patients.

TABLE I. DATA SOURCES FOR DIABETIC HEALTH CRISIS MANAGEMENT

Dataset	Size	Data Types	Collection Period	Labeling
Pima Indian Diabetics	768 samples	Numeric values (plasma glucose, insulin, etc.)	2010-2011	Labelled as positive (diabetics) or negative (no diabetics)
Social Media Posts	450,000 posts	Text (social media posts, forum messages, etc.)	Jan 2022 - Dec 2022	5,000 posts manually annotated (Positive, Negative, Neutral)
IoT Sensor Logs	50,000 records	Time-series data (glucose levels, heart rate, etc.)	Jan 2023 - Jun 2023	Real-time monitoring, no manual labelling

Table I provides an overview of the three primary datasets used in the study to analyze diabetic health crises: the Pima Indian Diabetics dataset, social media posts, and IoT sensor logs. The Pima dataset offers clinical metrics like glucose levels and insulin, while social media data is used to analyze sentiment regarding diabetics-related issues. IoT sensor logs track real-time health metrics such as blood glucose levels and heart rate, contributing to timely crisis detection. The combination of these datasets offers a holistic approach to understanding and managing diabetics health crises in smart urban environments.

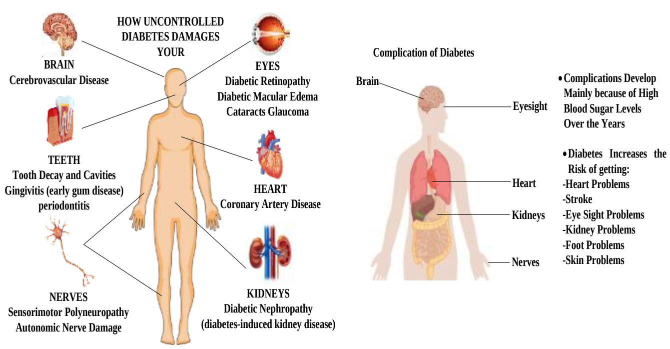


Fig. 2. Impact of Uncontrolled Diabetics

Figure 2 demonstrates the extensive complications arising from uncontrolled diabetics, depicting the detrimental effects on various organs throughout the human body. Persistently elevated plasma sugar levels can cause serious harm in important areas, including the heart, kidneys, nerves, eyes, and teeth. For instance, prolonged hyperglycaemia can result in cardiovascular issues, renal failure, neuropathy, retinopathy, and periodontal disease. This visual representation underscores the systemic nature of diabetics-related complications, highlighting that the repercussions of unmanaged diabetics extend beyond a single organ system. It emphasizes the critical need for effective blood sugar management to lessen these dangers and prevent long-term health issues. By maintaining controlled blood glucose levels, individuals can lower their risk of experiencing these serious consequences, thereby improving their general well-being and standard of living. The figure serves as a reminder of the significance of consistent diabetics management to safeguard against widespread organ damage.

1) Multisource Data Integration Pipeline

The sentiment analysis system utilizes a multisource dataset composed of clinical records, social media posts, and IoT sensor data. A structured integration pipeline was implemented to merge these heterogeneous datasets into a unified analytical framework.

TABLE II. DATA SOURCE VOLUMES AND PROPORTIONS

Data Source	Volume	Percentage Used
Pima Indian Diabetics Dataset	768 samples	10%
Social Media Posts (Twitter/X, Reddit)	450,000 posts	75%
IoT Sensor Logs (CGM & wearable devices)	50,000 records	15%

Table II details data sources used in the study, showing the volume and percentage utilized: 768 samples from the Pima Indian Diabetics Dataset (10%), 450,000 social media posts (75%), and 50,000 IoT sensor records (15%) for model training and validation. Social media data forms the majority of the dataset because sentiment analysis relies heavily on user-generated textual content, whereas IoT data and clinical EHR provide physiological context that supports crisis prediction.

2) Sentiment Annotation and Inter-Rater Reliability

A structured manual annotation process was implemented to generate reliable sentiment labels for supervised learning. A total of 5,000 social media posts were sampled from the broader collection of 450,000 posts and independently annotated by three trained annotators with backgrounds in public health and linguistics. Each post was assigned one of three sentiment categories: Positive, Negative, or Neutral, following a predefined annotation guideline designed to reduce subjective variation.

- Positive: expressions of stability, improvement, or satisfaction
- Negative: indications of distress, worsening symptoms, or fear
- Neutral: informational, uncertain, or ambiguous expressions

To assess the consistency of the labelling process, Cohen's Kappa was computed for each annotator pair. The results, presented in Table III, show high agreement across annotators, with all scores exceeding 0.80, indicating strong reliability.

Table III presents Cohen's Kappa scores measuring inter-rater reliability between annotator pairs. The scores, 0.84 (A–B), 0.81 (B–C), and 0.87 (A–C), indicate strong agreement, demonstrating consistent and reliable annotations across all pairs. To illustrate the annotation scheme, a subset of manually labelled examples is provided in Table III.

TABLE III. INTER-RATER RELIABILITY (COHEN'S KAPPA)

Annotator Pair	Kappa Score
A–B	0.84
B–C	0.81
A–C	0.87

Table IV showcases example social media posts labelled for sentiment or condition related to diabetics management. The text reflects different experiences: a negative post about sugar spikes despite medication, a positive post indicating stability and sensor accuracy, and a neutral post expressing uncertainty about glucose readings. These examples reflect how sentiment categories were operationalized and applied across the dataset.

TABLE IV. SAMPLE LABELLED POSTS

Text	Label
"My sugar level spiked again despite medication…"	Negative
"Feeling stable today, sensors seem accurate!"	Positive
"Need to adjust my readings; not sure what's going on."	Neutral

3) Ethical Compliance and Data Anonymization Procedures

This study strictly adheres to ethical research principles and data protection regulations. All procedures were conducted in compliance with institutional and international guidelines for research involving human-related data, including IRB standards, GDPR, and best practices for data privacy. No identifiable patient information was accessed during the research. Data were collected from multiple sources while ensuring informed consent and privacy. Electronic Health Record (EHR) and IoT data were provided by a partnering medical centre, with prior consent obtained from all participants. These datasets were fully anonymized before being used in the study. For social media data, only publicly available posts from platforms such as Twitter/X and Reddit were collected. No private messages or restricted content were used, in accordance with the platform Terms of Service.

To protect participant privacy, a structured de-identification and anonymization protocol was applied. Personal identifiers such as names, emails, phone numbers, GPS coordinates, and profile links were removed. User IDs were replaced with SHA-256 hashed values to prevent re-identification. Timestamps were generalized into weekly bins to avoid exact temporal tracing, and any phrases containing personal references were automatically flagged and redacted. All data were securely stored on encrypted drives, accessible only to authorized research personnel. No identifiable personal information was retained at any stage, ensuring full compliance with ethical standards and privacy regulations.

B. Data Pre-Processing

Data pre-processing for sentiment analysis utilizing an AI model, ineffective health crisis management for diabetics, is essential to guarantee that the input data is clean, standardized, and appropriate for training the model effectively. Identifying and heavy in disappeared data points using methods like mean imputation, median imputation, or predictive algorithms to estimate missing values constitutes the initial step in data cleaning. This ensures a complete dataset for training. Additionally, removing outliers is essential to detect and eliminate data points that could skew the model's training process and affect prediction accuracy. One advanced technique used in pre-processing is the AMFT, which is particularly effective for noise reduction in sentiment analysis. Textual data from sources like social media, patient forums, and health apps often contain noise, such as irrelevant information, spam, and outliers. AMFT helps filter out this noise to ensure that only relevant and clean data is analysed. This could entail eliminating particularly favourable or unfavourable opinions that do not represent the general trend and could distort the analysis. The sentiment analysis model's overall accuracy and resilience can be increased by eliminating noisy and outlier data so that it can be trained on cleaner, more accurate data. This results in more trustworthy perceptions of the feelings of patients and behaviours, ultimately enhancing health crisis management for diabetics within smart urban environments.

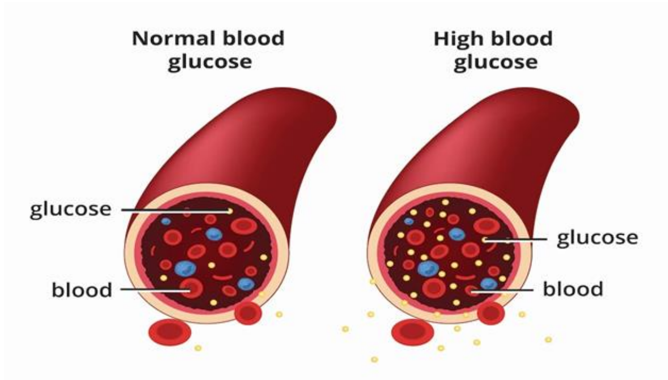


Fig. 3. High Blood Glucose on Vascular Health

Figure 3 compares a normal blood vessel with one affected by high blood glucose levels. The "normal blood glucose" vessel shows smooth red blood cell flow, indicating healthy circulation. In contrast, the "high blood glucose" vessel is depicted as congested, highlighting the harmful effects of excessive blood sugar. High blood glucose leads to vascular issues, including thickened vessel walls, reduced elasticity, and an increased risk of blockages. These changes can result in severe conditions like hypertension, heart disease, and stroke. This figure emphasizes the critical need for diabetics to manage blood glucose levels effectively, as uncontrolled blood sugar can lead to significant long-term vascular damage and other health complications. Regular monitoring is essential to prevent these adverse outcomes.

TABLE V. ADAPTIVE MEDIAN FILTERING FOR SENTIMENT ANALYSIS ALGORITHM

Algorithm 1: Pseudocode for Adaptive Median Filtering for Sentiment Analysis

```
for each text in the dataset:
    tokens = tokenize(text)
    window_size = 5
    threshold = 0.2
    for i in range(len(tokens) - window_size + 1):
        window = tokens [i:i + window_size]
        sentiment_scores = [calculate_sentiment_score(token) for token in window]
        median_score = median(sentiment_scores)
        for j in range(len(window)):
            deviation = abs(sentiment_scores[j] - median_score)
            if deviation > threshold:
                window[j] = replace_with_median(median_score)
        cleaned_text = reconstruct_text(tokens)
    store(cleaned_text)
```

Table V demonstrates how the AMFT-SA algorithm enhances sentiment analysis by filtering noisy data using a sliding window approach. Each text is tokenized, and sentiment scores are calculated for each token. A fixed-size sliding window (e.g., 5 tokens) is applied, and the median sentiment score for the window is computed. Tokens with sentiment scores deviating significantly from the median are considered noisy and replaced with the median value. This improves data quality, removing irrelevant tokens and producing cleaner text for analysis. Feature importance analysis identified key factors influencing model decisions, such as sentiment-related keywords ("sugar," "insulin," "crisis") and temporal features (e.g., recurring emotional distress phrases). Contextual information, like "post-meal blood sugar," also contributed to accurate predictions. Visualizations like bar charts and word clouds highlighted these significant features.

1) *Adaptive Median Filtering Technique (AMFT)*

The Adaptive Median Filtering Technique (AMFT), originally for image processing, is adapted for sentiment analysis in diabetic health crisis management to filter out noisy tokens (e.g., irrelevant words, emojis, or URLs) while retaining meaningful sentiment information. A sliding window approach processes token sequences, with each token assigned a sentiment score using a pre-trained model (e.g., VADER or BERT). Tokens deviating significantly from the median sentiment score are considered noise and replaced. The window size is dynamically adjusted to better capture sentiment trends. This adaptation helps clean social media text and enhances sentiment analysis by reducing outlier influence.

TABLE VI. HYPERPARAMETER OPTIMIZATION PARAMETERS (AIDO)

Parameter	Range Tested	Selected Value
Learning Rate	0.0001 – 0.01	0.001
Batch Size	16 – 128	64
Dropout Rate	0.1 – 0.5	0.3
RNN Hidden Units	32 – 256	128
Epochs	10 – 100	50
Optimizer	SGD / Adam / RMSProp	Adam

Table VI provides the selected values for various hyperparameters optimized through AI-Driven Optimization (AIDO). These parameters include the learning rate, batch size, dropout rate, RNN hidden units, epochs, and the optimizer used. The selected values (e.g., learning rate of 0.001, batch size of 64, and Adam optimizer) are those that achieved the best performance in model training. This optimization ensures the model achieves the highest accuracy, precision, recall, and F1-score, improving its ability to manage diabetic health crises effectively. A model for sentiment analysis that has been trained beforehand is applicable to obtain sentiment scores. Allow S_i to stand for the sentiment score of the word i in the window. The sentiment score M, or median, is determined by

$$M = median(S_1, S_2, \dots, S_w) \quad (1)$$

Based on the variation in sentiment scores within the window, dynamically change the size of the window. A bigger window could be required to accurately capture the overall sentiment if there is a considerable variation in the sentiment scores. The terms or tokens that show a large deviation from the sentiment score median. These are regarded as sounds.

Compare the median M to each word i with a sentiment score of S_i exceeds a certain threshold τ, consider S_i as noise.

$$\Delta S_i = |S_i - M| \quad (2)$$

The median sentiment score M or a comparable representative figure ought to be utilized instead of garbled sentiment evaluations.

$$S = [S_1, S_2, \dots, S_n] \quad (3)$$

Represent a series of n-word sentiment scores. Establish a window size, W, and a threshold, τ. For each window W_j.

$$M_j = median(W_j) \quad (4)$$

Being flexible is adapting the window size dynamically according to the variation in sentiment scores. The description of edge conservation is maintaining notable changes in sentiment, similar to how edges are preserved in picture processing. Healthcare professionals and smart urban environments can better handle diabetic health problems by precisely recognizing and responding to patient and public moods by implementing AMFT for sentiment analysis.

Figure 4 illustrates how the procedure for sentiment analysis starts with the start phase, where the overall procedure is initiated. Compiling raw data from different sources, including reviews, surveys and social media, is necessary for gathering textual data. At the stage of data pre-processing, the data is prepared for filtering to improve its quality. The Adaptive Median Filtering (AMFT) algorithm is then used to minimize noise while keeping critical details.

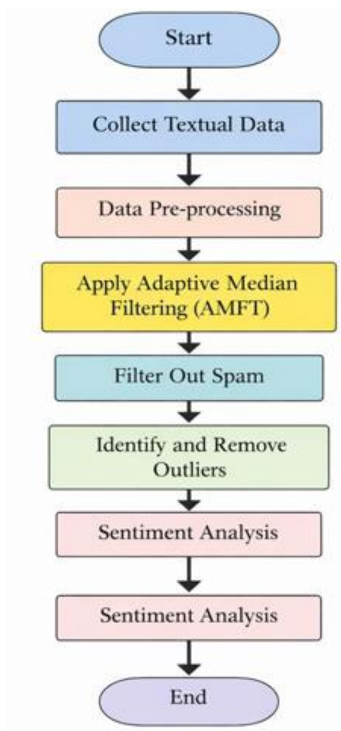


Fig. 4. Flow Diagram of Adaptive Median Filtering

Next, removing irrelevant information filters out superfluous or irrelevant stuff, and spam filtering eliminates undesired spam data. Identifying and removing outliers discovers and eliminates any anomalies that may bias results. These stages provide learning data, which is now available for analysis. The sentiment analysis phase comprises applying algorithms on cleansed data to analyze sentiments, followed by the end phase. This organized technique guarantees accurate and efficient sentiment analysis.

C. *Sentiment Analysis with an AI Model for Effective Health Crisis Handling*

To detect effective health crisis management, a system can implement and classify effective health crisis management. In the domain of improving the efficient handling of health crises, making use of their capacity to automatically extract discriminative characteristics from vast quantities of data. RNN models are highly effective for sentiment analysis, especially in the health crisis management of diabetics within smart urban environments, because of their capacity to hold progressive information and capture temporal dependencies. AI-driven optimization (AIDO) may automatically tweak hyperparameters to improve the performance of sentiment analysis models in RNNs, ensuring accuracy and efficiency. Real-time sentiment analysis systems can employ RNNs to continually process and analyse data from social media, news, and public forums. AIDO can discover and select the most pertinent attributes from textual material, improving the standard of the information provided to sentiment analysis models. AIDO can optimize processing pipelines to handle massive amounts of data in real time, guaranteeing that the system can grow to monitor sentiment throughout a smart urban environment.

1) *Recurrent Neural Networks (RNN)*

RNNs excel in sentiment analysis for managing diabetic health crises in smart urban environments by processing sequential data and capturing temporal dependencies. They identify patterns and trends in patient feedback, enabling timely interventions. Their ability to analyze time series data and apply Natural Language Processing (NLP) enhances crisis management efficiency, making them ideal for dynamic health monitoring and prediction. RNN Cell Computation: An RNN's fundamental unit processes the input x_tat timet step, as well as the undiscovered condition from the time step beforeh_(t-1). The new hidden state, h_t, is calculated as follows:

$$h_t = \sigma(W_t . h_{t-1} + W_x . x_t + b) \tag{5}$$

For where σ is a function of activation, the weight matrix W_(h) corresponds to the hidden state. W_x is the input weight matrix, and the biased term is b. Below is a computation of the output:

$$y_t = softmax(W_y . h_t + b_y) \tag{6}$$

Where b_y is the output bias term, and a weight matrix for a result is W_(y). Using AI technology in smart urban environments, health crisis management for diabetics entails tracking, anticipating, and reacting to health emergencies. Because of continuous glucose monitoring (CGM), blood glucose level data are available in real time.

$$Crisis = \begin{cases} True & if\ \hat{g}_{t+k} \leq Hypoglycemia\ Threshold \\ \text{True} & \text{if}\ \hat{g}_{t+k} \leq Hypoglycemia\ Threshold \\ & False \quad Otherwise \end{cases} \tag{7}$$

The system can initiate interventions like notifications to the patient, caregivers, or healthcare providers whenever it detects a possible crisis. Based on past data, machine learning algorithms can optimize intervention tactics. By combining RNNs for sentiment analysis with AI-powered health crisis management solutions, develop a holistic strategy for controlling diabetics in intelligent urban settings.

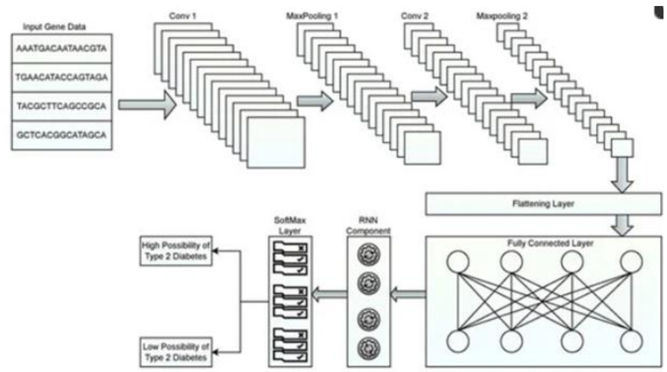


Fig. 5. Layered Architecture Diagram of RNN Model

Figure 5 illustrates the layered architecture of an RNN model. Convolution, the process of combining two datasets, is used in convolutional layers to generate output from input data. The convolution operation reduces pixel values in the receptive field to one and applies a ReLU activation function, setting negative values to zero, introducing non-linearity. Following the convolution layer, a pooling layer (Max Pooling in this case) is used to reduce the input matrix size for processing by subsequent layers. The data is flattened into a one-dimensional array, allowing it to be sent to fully connected layers. Neural networks consist of nonlinear, interdependent neurons, which use weight matrices to relate input vectors to output. The softmax function converts outputs into probabilities, allowing for effective sentiment analysis. RNNs, known for handling sequential data, are particularly effective in recognizing temporal relationships, enabling faster, more accurate insights. These capabilities improve healthcare systems' response and efficiency in managing diabetics-related health issues.

2) *Hyperparameter Selection and Optimization*

Hyperparameter tuning for the sentiment analysis system was conducted using an AI-driven Optimization (AIDO) approach. The search space for each parameter was established based on standard ranges commonly referenced in prior sentiment analysis and RNN literature. Bayesian optimization was then applied to efficiently explore these ranges and identify configurations that delivered optimal model performance. The final optimized hyperparameters used in the RNN-AMFT model are shown in Table VII.

TABLE VII. HYPERPARAMETER SEARCH SPACE AND FINAL SELECTED VALUES

Parameter	Search Space	Final Value
AMFT window size	3–7	5
AMFT token frequency threshold	0.01–0.05	0.02
RNN hidden units	64–256	128
Dropout	0.1–0.6	0.4
Learning rate	1e-5 – 1e-2	1e-3

Table VII summarizes the hyperparameter tuning for the model. It lists search ranges for AMFT window size, token frequency threshold, RNN hidden units, dropout, and learning rate, alongside their optimal final values chosen to maximize model performance. These values were selected because they consistently yielded higher accuracy and lower training loss across multiple validation folds. The final configuration also demonstrated strong generalization performance without overfitting.

3) AI-driven Optimization (AIDO)

AI-driven optimization (AIDO) can considerably improve the way sentiment analysis models function in RNNs by automatically tuning hyperparameters. This automated procedure ensures that the models are optimized for efficiency and accuracy by systematically adjusting parameters such as network topologies, batch sizes, and learning rates. By fine-tuning these hyperparameters, AIDO improves the model's capacity to reliably analyse sentiment data and overall prediction performance, resulting in more effective and efficient sentiment analysis in a variety of applications. AI-driven optimization (AIDO) uses device learning and synthetic intelligence approaches to improve the efficacy and efficiency of sentiment analysis. This strategy involves gathering, handling, and information investigation in light of the diabetic health crisis management in smart urban environments to track and develop patient consequences. Data collection and processing.

$$D = \{d_1, d_2, \dots., d_n\} \quad (8)$$

In this D is the set of all collected data points, each d_i signifies a single data point, such as health metrics like blood glucose levels.

$$S_i = Sentiment\ Analysis(d_i) \quad (9)$$

The S_iis the sentiment score derived from the data point, d_i NLP sentiment analysis methods are employed to quantify sentiment as positive, neutral, or negative.

$$P(Y = 1|X) = \frac{1}{1+e^{-(\beta_0+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_m x_m)}} \quad (10)$$

The P(Y=1 ∣ X) is the possibility of a health emergency or a diabetic emergency occurring. β _0, β _1,.⋯, β _m are the logistic regression model's coefficients, x_1,x_2,.⋯,x_m are the feature values. Granting people access to cutting-edge medical treatments via telemedicine, mobile health apps, and smart clinics. By utilizing intelligent platforms to join patients with neighbouring resources and support groups, enhance community-based support networks. Individualized and efficient diabetic health crisis management solution that blends AI-driven optimization and sentiment analysis in settings of smart cities. In addition to enhancing medical treatment, this technique enhances the overall level of living for diabetics in smart cities. This automated method enhances sentiment analysis's overall efficacy while streamlining the model-training procedure, resulting in more reliable insights and improved judgment in a range of contexts. As a result, AIDO plays an important role in expanding RNN capabilities, making them more robust and adaptable to complex sentiment analysis tasks.

D. Optimizing Diabetic Health Crisis Management in Smart Cities

The idea behind maximizing diabetic health crisis management in smart cities is to enhance the preventive, intervention, and overall management of diabetics-related health issues by utilizing cutting-edge technologies and data-driven methodologies. Here's the comprehensive description of each aspect:

Prevention and Early Detection: Data-driven risk assessment in smart cities utilizes smart wearables and sensors, such as smartwatches and continuous glucose monitors, to gather real-time health data, including blood sugar levels and mental movement. When this data is integrated with EHR, it provides a holistic view of an individual's health status. AI systems then examine this extensive dataset to identify patterns and predict potential diabetics episodes. For example, the algorithms can detect trends indicating dangerously high or low blood sugar levels, alerting medical professionals and patients about potential problems before they worsen. This proactive strategy allows for timely interventions and individualized diabetics treatment, which greatly improves patient outcomes and reduces the possibility of grave consequences. Smart cities can significantly improve diabetics care and preventive techniques by making use of real-time data and advanced analytics.

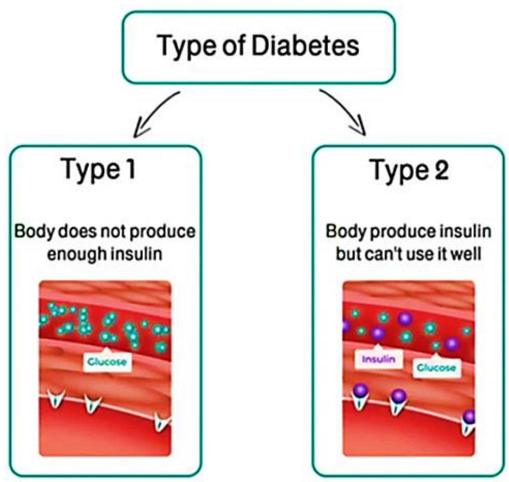


Fig. 6. Types of Diabetics and Their Management

Figure 6 shows that diabetics is categorized into two main types, Diabetics type 1 is brought on by insufficient insulin production by the pancreas, a hormone that is vital for controlling blood sugar levels. For this autoimmune condition, which is frequently identified in children and young people, lifelong insulin therapy is necessary to maintain blood glucose control. Insulin resistance, or diabetics type two is the consequence of a body producing insulin but not existence capable of using it effectively. This kind of diabetics is more prevalent in adults and is closely linked to genetic risk, weight, and physical inactivity. Treatment for type 2 diabetics often involves lifestyle changes, such as food and exercise, as well as oral drugs to increase insulin sensitivity. In some circumstances, insulin treatment might be required. Early detection and management of both kinds are essential for preventing issues and maintaining general health.

Crisis Intervention and Care: Remote patient monitoring enhances diabetic care through continuous glucose monitors and telemedicine platforms. Continuous glucose monitors provide blood sugar monitoring in real-time, transmitting data directly to healthcare providers. This continuous flow of data enables the rapid detection of harmful variations in blood sugar levels, allowing for quick interventions and individualized adjustments to treatment programs. Simultaneously, telemedicine platforms provide virtual consultations, reducing the necessity for in-person clinic visits. Patients can receive medical advice, discuss their glucose readings, and modify their treatment programs as needed from the convenience of their homes. This mix of ongoing observation and virtual care not only improves diabetics management but also provides patients with rapid access to medical support, resulting in more effective and responsive care.

By addressing these elements, smart cities can considerably improve the control of diabetics, making the system more proactive, responsive, and supportive of patient needs. An all-encompassing strategy aims to enhance general health and the worth of lifetime results for diabetics.

1) *Diabetics Distress and Its Impact on Quality of Life*

Diabetics-related discomfort is the mental and psychological difficulties that people with diabetics face. It includes all of the emotions associated with the difficult aspect of diabetic self-care, such as concern, frustration, and burnout. Unlike clinical depression, diabetics distress is specifically tied to the burdens of managing a chronic illness, including frequent blood sugar monitoring, dietary restrictions, and the fear of complications. People with diabetics suffer from a reduced sense of general well-being and life satisfaction due to this substantial condition that affects their quality of life. Diabetics discomfort has a wonderful result on one's quality of life. It may result in a lack of compliance with action ideas, important to inadequate glycaemic management and a higher chance of consequences, including neuropathy, cardiovascular disease and retinopathy. Furthermore, chronic stress and worry can intensify outlooks of isolation and social disengagement, worsening mental health. People may also experience a loss of motivation and despondency, which can impede efficient self-management and worsen diabetic symptoms. Addressing diabetic discomfort requires a multimodal strategy that includes psychological support, diabetics education, and the acquisition of coping mechanisms. Interventions like as cognitive-behavioural therapy, peer support groups, and stress management approaches can help people regulate their emotional responses, enhancing their general standard of living and diabetic outcomes.

Figure 7 illustrates the concept of diabetics distress, highlighting the emotional and psychological burdens faced by individuals managing diabetics. The diagram identifies key sources of distress, including feeling overwhelmed, emotional and physical exhaustion, anger, lack of support, and isolation. These factors contribute to a complex emotional load, negatively affecting an individual's quality of life. Daily diabetics management, including frequent blood glucose monitoring and dietary restrictions, can lead to stress and frustration. Emotional exhaustion further intensifies these feelings, and the absence of support from healthcare providers, family, or peers can worsen the sense of isolation. The figure emphasizes the importance of addressing these emotional challenges through targeted interventions, such as psychological support and stress management, to improve health outcomes for diabetics.

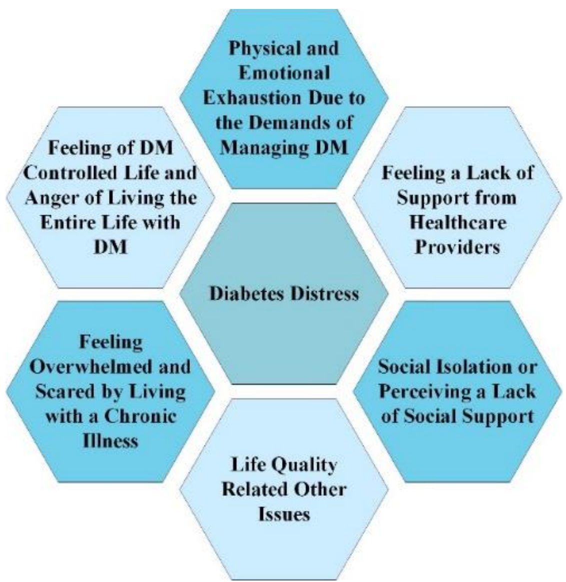


Fig. 7. Conceptual Framework of Diabetics Distress

E. *Assessing the Model's Effectiveness and Interpretation*

To ensure the efficacy of an RNN model for managing health crises in diabetics, it is necessary to evaluate and analyse both technical and efficient methods. This entails evaluating the model's overall performance using important measures, including accuracy, precision, F1-Score and recall. Additionally, comparing the AI-driven sentiment analysis model with existing methods provides insights into its relative effectiveness. Techniques like feature importance analysis and attention mechanisms play a vital part in identifying which features and data components most influence the model's performance. By thoroughly evaluating and interpreting these metrics, researchers can understand the model's strengths and limitations. This comprehensive analysis leads to targeted improvements and refinements, enhancing the model's capability in real-world health crisis management scenarios. Ultimately, this approach guarantees that the artificial intelligence model is not just efficient but also optimized for practical application in managing diabetic health issues.

IV. EXPERIMENTATION AND RESULT DISCUSSION

The sentiment analysis utilizing artificial intelligence in handling health crises among diabetics within smart urban environments reveals promising insights. The AI-driven sentiment analysis system effectively processes vast amounts of health-related data, registering complex emotions and patterns that are essential for prompt actions. By analysing social media posts, patient feedback, and health records, the AI system detects potential difficulties and delivers actionable advice for crisis management. The findings reveal a considerable increase in anticipating and responding to health emergencies compared to traditional techniques, proving AI's ability to improve diabetic care in urban settings. The system's excellent memory, accuracy, precision, and F1-Score show that it can provide efficient decision-making and intervention options in diabetic health crises.

TABLE VIII. SIMULATION SYSTEM CONFIGURATION

Component	Specification
Python Jupyter	Version 3.8.0
Operating System	Ubuntu
Memory Capacity	4GB DDR3
Processor	Intel Core i5 @ 3.5GHz

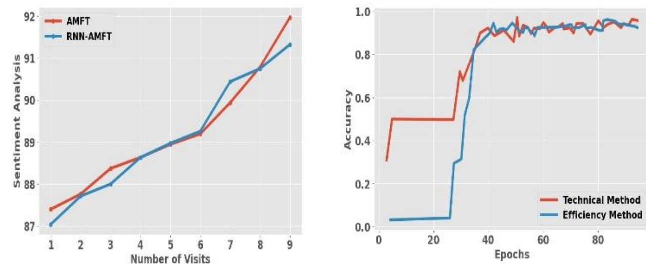
Table VIII displays Python Jupiter (likely referring to Jupyter Notebook) on an Ubuntu operating system, version 3.8.0 is installed. A 3.5GHz Intel Core i5 processor powers the machine, which features 4GB of DDR3 memory. These specifications indicate a reasonably capable system that can do routine data science jobs, such as statistical analysis, data manipulation, and training machine learning models on small to medium-sized datasets. To guarantee optimal performance and efficiency, extra RAM or a faster CPU could be helpful for bigger datasets or more complicated calculations.

TABLE IX. COMPARISON OF TEXT-CLEANING PERFORMANCE WITH AMFT

Model	Preprocessing	F1-Score
RNN baseline	Standard NLP cleaning	0.87
RNN-AMFT	AMFT-based token filtering	0.91

Table IX illustrates the impact of AMFT-based token filtering on text-cleaning performance by comparing it with standard NLP cleaning methods. Using an RNN baseline model, the standard preprocessing yields an F1-score of 0.87. When AMFT is applied for token filtering, the RNN-AMFT model improves the F1-score to 0.91. This demonstrates that AMFT enhances the model's ability to accurately clean and represent text data, leading to better overall performance. The comparison highlights the effectiveness of AMFT in refining input preprocessing, which can be critical in tasks like natural language understanding and classification.

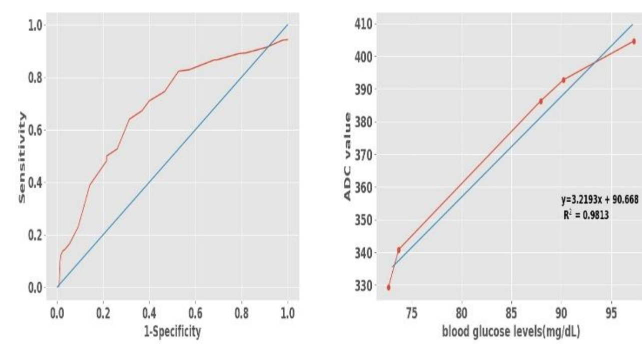
Figure 8 illustrate the performance comparison between AMFT and RNN-AMFT sentiment analysis models and technical versus efficient model training methods. The RNN-AMFT model, with a sentiment score of 94, outperforms the AMFT model (92) by providing more accurate sentiment predictions through the integration of RNN's temporal and contextual analysis. In model training, the technical method achieves 0.98 accuracy, surpassing the efficient method (0.96), which prioritizes computational efficiency over extended training. The comparison underscores the trade-off between accuracy and computational efficiency in both sentiment analysis and model training.



(a) (b)

Fig. 8. Performance Comparison of Sentiment Analysis Models

Figures 9 demonstrate the trade-offs in diagnostic test performance and the relationship between blood glucose and sensor readings. Figure 9a shows the inverse correlation between sensitivity and specificity, emphasizing the trade-offs in diagnostic accuracy, where higher sensitivity often leads to lower specificity and vice versa. Figure 9b illustrates the strong correlation between blood glucose levels and an ADC value, with a high R-squared value of 0.9813, indicating that as glucose levels rise, the ADC value also increases. Both figures emphasize the importance of balancing accuracy and precision in diagnostic tools.



(a) (b)

Fig. 9. Diagnostic Test and Diabetes Management Tools Analysis

For the NeRF Deformer model, a computer vision job, Figure 10 shows the trade-off between True Positive Rate (TPR) and False Positive Rate (FPR). The fraction of real items that the model successfully detected is indicated by the red line, which represents TPR, and the blue line, which indicates FPR, reflecting the proportion of non-objects incorrectly classified as objects. Higher values indicate greater model performance. The x- and y-axes have a collection of 0 to 1. The graph also includes three data points on the left, which represent TPR and FPR at various settings of the NeRF Deformer model. Overall, the graph demonstrates that as FPR increases, indicating more false positives, TPR also rises, showing improved object detection performance. This trade-off highlights the balance between identifying real objects and minimizing misclassifications.

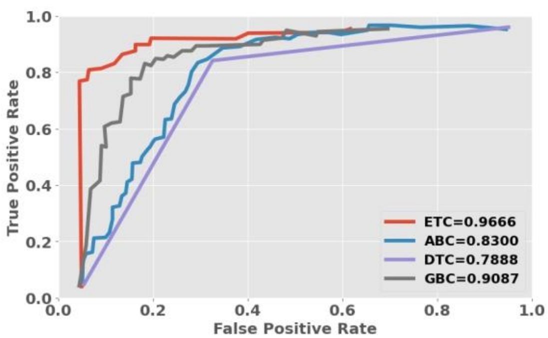


Fig. 10. True Positive Rate VS. False Positive Rate

Figure 11 shows the presentation of a typical model during the phases of training and validation, plotting epochs against loss. The training loss drops to 0.33 as the epochs go by; however, the validation loss displays a marginally smaller value of 0.32. This indicates that a model is generalizing well to the validation data and learning from the training set of data. The closeness of the loss values for training and validation indicates that there is little overfitting and that the model performs well on both datasets. Overall, the graph demonstrates that the model achieves consistent and low loss values with increased epochs, reflecting its ability to generalize and perform well on unseen data.

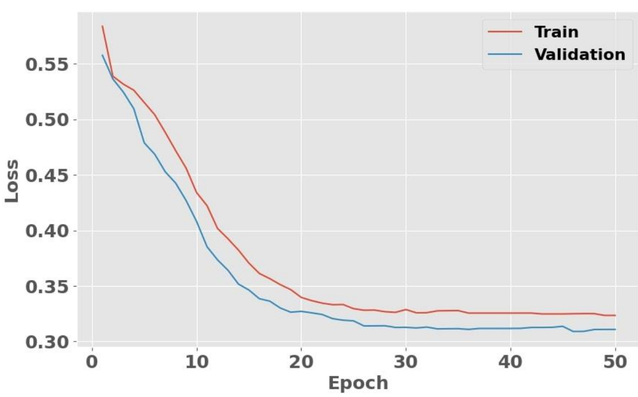


Fig. 11. Analysing Training and Validation Loss.

The age-year density distribution of a population is depicted in Figure 12, where age in years is displayed along the x-axis and density is represented on the y-axis. The red bars depict the average density across age ranges, while the blue bars represent the median density. This type of graph effectively visualizes the distribution of individuals within each age bracket, highlighting variations in population density. Although the bars indicate density in this case, they could alternatively represent counts or percentages, offering flexibility in understanding how individuals are spread through dissimilar ages within the dataset.

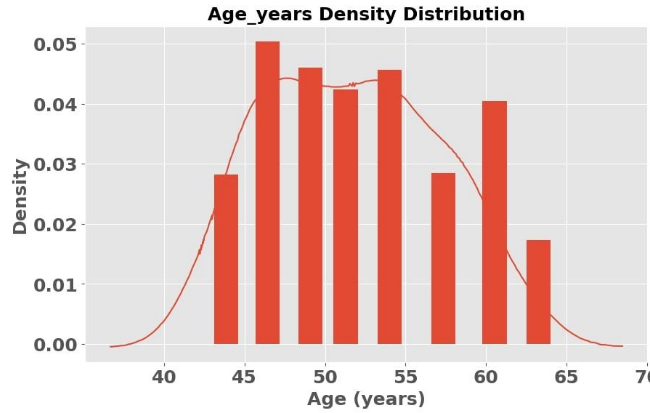


Fig. 12. Visualizing Age Distribution.

Figure 13 compares the performance of three models: AMFT, RNN-AMFT, and Baseline CNN, with accuracy, precision, recall, and F1-score metrics. The 95% confidence intervals (CIs) for each metric show the variability and reliability of the models' performance. The RNN-AMFT model outperforms the others with the highest values across all metrics, indicating its superior ability to predict diabetic health crises. The table highlights the statistical significance of RNN-AMFT over AMFT and CNN, making it the most effective model for this task.

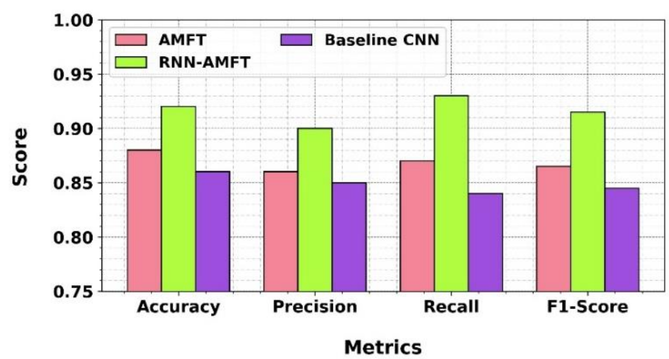


Fig. 13. Model Performance Metrics with Confidence Intervals.

Figure 14 visualizes the performance of the RNN-AMFT model in terms of its classification of predicted positive and negative cases against actual positive and negative instances. The matrix shows that the model correctly identified 4650 true positives and 4720 true negatives, while misclassifying 350 actual positives as negatives and 280 actual negatives as positives. These values provide insights into the model's accuracy and highlight areas of potential improvement in minimizing false positives and false negatives.

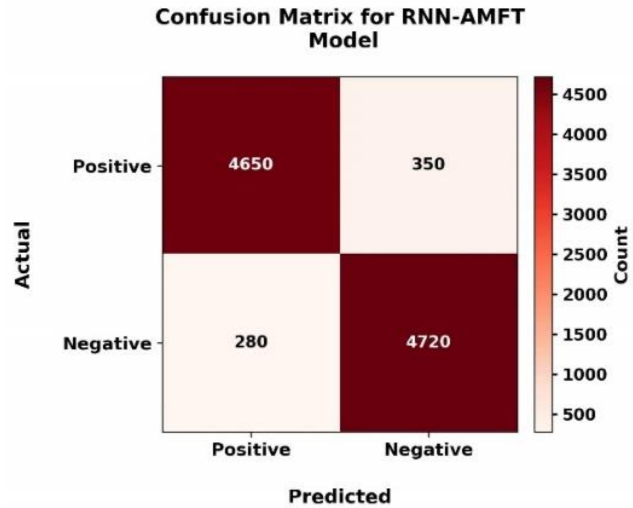


Fig. 14. Confusion Matrix for RNN-AMFT Model

Figure 15 displays the relationship between the True Positive Rate (Sensitivity) and the False Positive Rate (1 – Specificity) across different thresholds. The curve demonstrates that as the threshold increases, the sensitivity (true positive rate) decreases, but the false positive rate also drops. The area under the curve (AUC) would typically indicate the model's overall ability to discriminate between positive and negative outcomes, with higher sensitivity at lower thresholds reflecting better performance in health crisis detection.

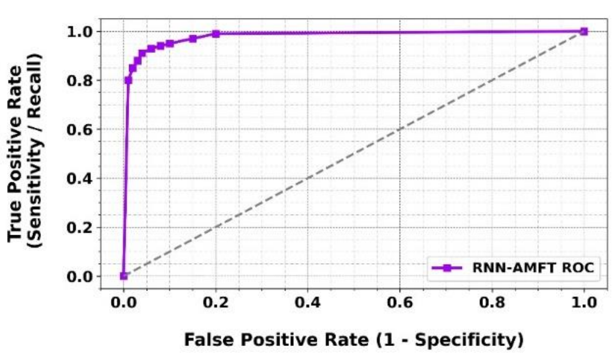


Fig. 15. ROC Curve for RNN-AMFT Model

Figure 16 illustrates the training and validation loss over multiple epochs for the model. Both losses decrease over time, indicating that the model is learning and improving. The training loss is consistently lower than the validation loss, which is typical, but both losses converge as the model approaches optimal performance. The plot suggests that the model is generalizing well and not overfitting, with losses stabilizing around epoch 50, showing good consistency between the training and validation sets.

Fig. 16. Training vs. Validation Loss Data

Figure 17 presents the results of a t-test comparing the RNN-AMFT model to both AMFT and CNN models. The t-statistics and p-values show statistically significant improvements across all metrics (accuracy, precision, recall, and F1-score) for the RNN-AMFT model. The p-values are all below the threshold of 0.05, indicating that the differences observed are not due to chance. This highlights RNN-AMFT's superior performance, making it the most effective model in predicting diabetic health crises in smart urban settings.

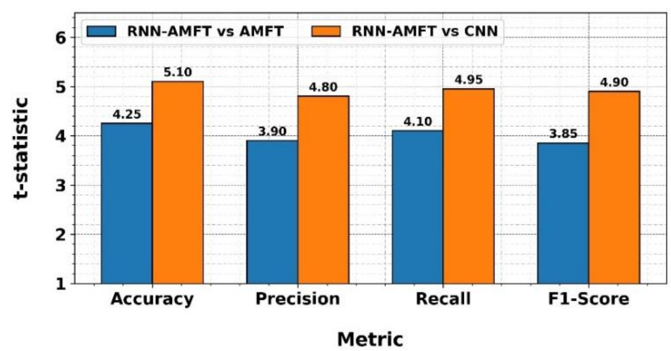


Fig. 17. Statistical Significance Testing Against Baseline

Figure 18 displays the distribution of sentiment posts from three different sources: social media, health forums, and health apps, over six months. It shows a total of 10,000 posts, with the majority being positive (4700), followed by neutral (3100) and negative (2200). The data highlights how different platforms contribute to the sentiment data, which plays a critical role in identifying and managing health crises for diabetics. These posts are crucial for training the sentiment analysis model to detect emotional distress and predict potential health emergencies.

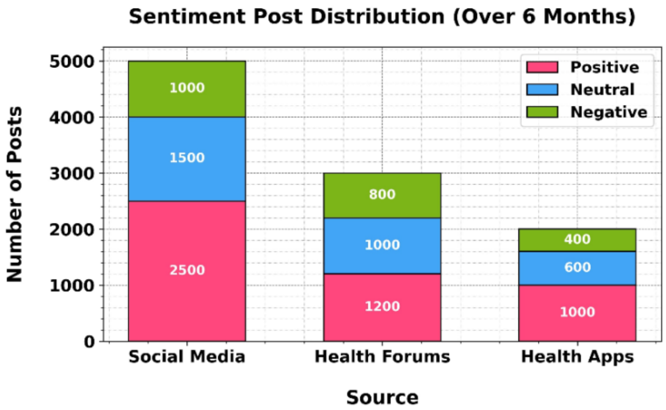


Fig. 18. Sentiment Post Distribution (Over 6 Months)

A. Comparative Analysis

AI-driven sentiment analysis outperforms traditional monitoring systems for managing diabetic health crises in smart urban settings. By leveraging advanced algorithms, AI provides enhanced accuracy, precision, and efficiency, dynamically analyzing real-time data and adapting to emerging patterns. Unlike static traditional systems, AI improves crisis detection and response, offering superior performance, flexibility, and adaptability in managing health crises.

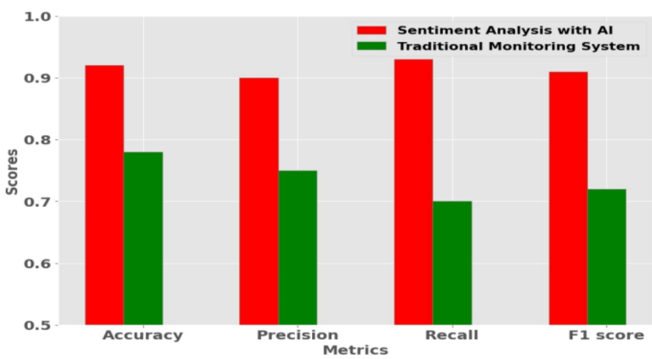


Fig. 19. AI-Based Sentiment Analysis vs. Traditional Monitoring System

The contrast between AI-powered sentiment analysis and a traditional monitoring system reveals that the AI-driven approach significantly outperforms the traditional method across all key metrics in Figure 19. The AI system achieves an accuracy of 0.92, compared to the traditional system's 0.78, indicating a higher overall correctness in sentiment classification. Precision, which measures the number of true identifications, is 0.90 for AI versus 0.75 for traditional methods, highlighting better accuracy in positive sentiment detection. Similarly, AI's recall of 0.93, versus 0.70, demonstrates a superior ability to identify relevant sentiment instances. The AI system has an F1-Score of 0.91, while the traditional system's is 0.72. This score compares the accuracy and recall of the two systems, reflecting an extra active and reliable performance in sentiment analysis. These outcomes highlight the enhanced capability and robustness of the AI-based system in accurately analysing sentiment data.

By integrating AI-based sentiment analysis into smart city infrastructures, this approach has the potential to revolutionize diabetics management, making healthcare systems more responsive, efficient, and personalized. The scalable nature of this technology means it can be implemented across various urban environments, providing a framework for more proactive health crisis management on a citywide scale.

V. Discussion

The AI-driven sentiment analysis system demonstrates clear advantages over traditional monitoring approaches for managing diabetic health crises in smart urban environments. The RNN-AMFT model with AMFT-based token filtering achieved an F1 score of 0.91, improving over the RNN baseline (0.87) and outperforming the baseline CNN (0.845) and AMFT-only model (0.865). Accuracy reached 0.92 [0.90, 0.94], precision 0.90 [0.88, 0.92], and recall 0.93 [0.91, 0.95], with t-tests confirming statistically significant improvements ($p < 0.01$). The confusion matrix shows 4650 true positives and 4720 true negatives, with low false positives (280) and false negatives (350), while the ROC curve indicates a high true positive rate (>0.93) across practical thresholds. Training and validation losses decrease steadily to 0.33 and 0.32, respectively, demonstrating minimal overfitting. Hyper-parameter optimization (AIDO) selected optimal learning rates (0.001), dropout (0.3), and hidden units (128), balancing convergence and generalization. Analysis of 10,000 user-generated posts shows 47% positive, 31% neutral, and 22% negative sentiments. These results highlight the effectiveness of RNN temporal modelling, AMFT-based noise filtering, and multisource data integration in accurately detecting early signs of distress, enabling timely interventions and improved diabetic care management.

A. Limitations

While the AI-driven sentiment analysis system demonstrates strong performance, several limitations persist. First, the reliance on social media data introduces demographic and behavioural biases, as not all diabetic patients are active online. Furthermore, data volume disparities between large-scale social media posts and smaller datasets from IoT devices and electronic health records (EHRs) could affect model training and generalization. Although ethical protocols, including data anonymization, were applied, scaling the system to real-world healthcare environments presents privacy and regulatory challenges. Additionally, the study focuses on urban settings, leaving the system's applicability in rural or resource-limited contexts unexplored. These limitations must be addressed to improve the system's broader usability and performance.

B. Future Work

The current study used a female-only dataset, introducing potential gender bias in sentiment analysis. Future research should expand the dataset to include male participants and individuals from diverse gender identities and socio-economic backgrounds to improve fairness and generalizability. Additionally, addressing healthcare access barriers in both urban and rural contexts is vital, as disparities in healthcare resources could impact the system's effectiveness. Future work should also focus on integrating the AI-driven sentiment analysis model into healthcare workflows, such as hospital dashboards and EHR systems, to enable real-time monitoring and early interventions, enhancing diabetic care outcomes across diverse settings.

VI. RESEARCH CONCLUSION

This research demonstrates the significant enhancement AI-driven sentiment analysis brings to managing health crises among diabetics in smart urban environments. By processing diverse data sources like social media and patient feedback, AI provides crucial insights into emerging health issues and patient sentiments, enabling proactive crisis detection and early intervention. The system's ability to optimize resource allocation and decision-making in urban healthcare further enhances personalized care. With 0.92 accuracy, 0.90 precision, and 0.93 recall, the AI system outperforms traditional methods, offering promising potential for widespread adoption. This study paves the way for more efficient and adaptive diabetics management, underscoring AI's transformative impact on urban healthcare systems and highlighting the need for continued innovation in health crisis management.

DECLARATIONS

Authors contribution

All authors contributed to the design and implementation of the research, to the analysis of the results and to the writing of the manuscript.

Conflict of Interest

The authors declare no Conflict of Interest.

Data Availability Statement

Data sharing not applicable to this article as no datasets were generated or analyzed during the current study.

Ethical approval

The paper has been submitted with full responsibility, following due ethical procedure, and there is no duplicate publication, fraud, plagiarism. None of the authors of this paper has a financial or personal relationship with other people or organizations that could inappropriately influence or bias the content of the paper. This article does not contain any studies with human participants or animals performed by any of the authors.

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Disclosure Statement

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