AI-Enabled Early Detection of Chronic Diseases Using Wearable Sensor Data

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Abstract: Early detection of chronic diseases remains a major public health challenge, particularly in urban communities where lifestyle-related risk factors are increasingly prevalent. This study proposes and evaluates an artificial intelligence (AI)-enabled framework for the early detection of chronic diseases using wearable sensor data collected in Quezon City, Philippines. The research integrates multimodal physiological and behavioral signals, including heart rate, physical activity, sleep patterns, and other relevant biosensor indicators, to identify early risk patterns associated with chronic conditions such as hypertension, diabetes, and cardiovascular disease. A supervised machine learning approach was employed to preprocess, analyze, and classify wearable sensor data obtained from [number] participants. Feature engineering and model optimization techniques were applied to improve predictive performance and reduce noise from real-world sensor streams. The developed model was evaluated using standard classification metrics, including accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC). The findings indicate that the proposed AI-based system achieved promising predictive performance in distinguishing individuals at elevated risk of chronic disease, demonstrating the feasibility of wearable technologies as scalable tools for preventive healthcare. In addition, the study highlights the potential of continuous, non-invasive monitoring to support earlier clinical intervention and personalized health management in resource-constrained urban settings. This research contributes to the growing field of digital health by offering an AI-driven, data-informed approach to chronic disease surveillance and early risk detection in the Philippine context.

Keywords: artificial intelligence, chronic disease detection, wearable sensors, digital health, machine learning, preventive healthcare
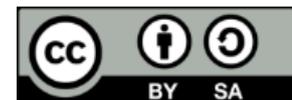
INTRODUCTION

Chronic diseases remain one of the most pressing public health challenges worldwide [1], [2], [3]. According to the World Health Organization (WHO), noncommunicable diseases account for the majority of global deaths [4], with cardiovascular diseases [5], cancers [6], chronic respiratory diseases [7], and diabetes representing the largest share of this burden [8]. The challenge is particularly significant in low- and middle-income countries, where premature mortality from chronic conditions remains disproportionately high. In the Philippines, chronic diseases have become a dominant cause of mortality, with noncommunicable diseases comprising most of the leading causes of death in recent years.

Traditional approaches to chronic disease detection often depend on episodic clinical visits [9], laboratory examinations[10], and symptom-driven consultations [11]. While these methods remain

essential, they may fail to capture subtle physiological changes that emerge gradually in daily life before a condition becomes clinically evident. This limitation creates a need for more continuous, accessible, and proactive monitoring strategies. In this context, digital health has gained increasing importance as a means of strengthening health systems, improving access, and supporting earlier intervention, especially in settings where healthcare resources are unevenly distributed.

Wearable devices offer a promising response to this need because they enable continuous, non-invasive, and real-time collection of physiological and behavioral data in free-living environments[12]. Recent literature shows that wearable technologies can capture health-related signals such as heart rate, physical activity, sleep patterns, body temperature, blood pressure, and peripheral oxygen saturation, making them increasingly relevant for chronic disease monitoring and remote patient management. Their value lies not only in data collection but also in their potential to shift healthcare from a reactive model toward preventive and personalized care[13].

However, wearable sensor data are often high-volume, heterogeneous, and noisy, which limits their direct clinical utility unless advanced analytical methods are applied. Artificial intelligence (AI) [14], particularly machine learning, offers a practical solution by identifying complex temporal patterns, extracting meaningful digital biomarkers, and generating risk predictions from multidimensional data streams. At the same time, the growing use of AI-enabled wearables raises important concerns related to data quality, interoperability, fairness, privacy, and responsible deployment. These issues are especially relevant when such technologies are introduced into real-world public health contexts rather than controlled experimental settings.

The Philippine setting provides a compelling context for this line of inquiry. Quezon City, a highly urbanized area within Metro Manila and one of the country's largest population centers, reflects many of the demographic and health system pressures associated with rapid urbanization, including rising chronic disease risks, diverse care needs, and the demand for scalable health technologies. Despite growing interest in digital health and wearable-based monitoring, there remains limited evidence on AI-enabled early detection frameworks developed and evaluated in urban Philippine contexts using wearable sensor data. This gap underscores the need for localized research that accounts for contextual realities while contributing to the broader field of data-driven preventive healthcare.

Against this background, the present study investigates the use of AI-enabled models for the early detection of chronic diseases using wearable sensor data collected in Quezon City, Philippines. Specifically, the study examines how continuous sensor-derived signals can be analyzed to identify early risk patterns associated with chronic disease development. By integrating wearable sensing with AI-based prediction, this research aims to contribute to the advancement of scalable, non-invasive, and context-sensitive approaches to preventive healthcare in urban communities.

RELATED WORK

Recent literature has shown that wearable devices are increasingly used for chronic disease monitoring because they enable continuous, non-invasive collection of physiological and behavioral signals in real-world settings. A recent systematic review covering 61 studies reported that wrist-worn bands were the most common form factor, typically integrating accelerometers, photoplethysmography (PPG) sensors, biopotential sensors, pressure sensors, and thermometers to capture activity, heart rate, body temperature, blood pressure, and peripheral oxygen saturation. Related review evidence also indicates that wearable technologies are already being applied across cardiology, respiratory medicine, neurology, and endocrinology, although persistent concerns remain regarding data accuracy, privacy, and integration with routine care systems.

The intervention literature further suggests that the current evidence base is unevenly distributed across disease groups and device categories. In a 2024 scoping review of 79 intervention studies on chronic disease self-management, diabetes was the most frequently studied condition, while wearable activity

trackers were the most commonly used devices. The reviewed studies assessed a wide range of outcomes, including clinical, behavioral, user-experience, health-system, and biopsychosocial measures. This pattern indicates that wearable-based chronic care research has progressed beyond simple signal acquisition, but it is still concentrated in a limited subset of conditions and use cases.

Artificial intelligence has substantially expanded the analytical value of wearable sensor data by enabling automated detection, classification, and prediction [15]. Disease-specific reviews show particularly strong momentum in cardiovascular and sleep-related applications. For example, a 2024 meta-analysis on machine learning for atrial fibrillation detection from ECG data reported pooled sensitivity and specificity of 97%, with deep learning approaches outperforming traditional machine learning methods. Likewise, a 2024 systematic review and meta-analysis on wearable AI for sleep apnea found promising pooled performance for detection and classification tasks, although the authors concluded that the technology was not yet ready for routine standalone clinical use. These studies demonstrate that AI-enabled wearables can capture clinically relevant patterns, but they also show that performance varies depending on algorithm type, sensor modality, and device placement[16].

Similar developments are evident in diabetes-related research. A systematic review on AI-enabled wearable technologies for blood glucose forecasting found that wrist-worn devices frequently relied on PPG and near-infrared sensing, with ensemble methods such as random forest commonly used for prediction. More recent review evidence has expanded this picture, showing that AI-integrated wearables support glycemic monitoring[17], adaptive insulin management, and prediction of diabetes-related events. However, these studies also highlight recurring limitations, including small sample sizes, limited demographic diversity, variable data quality, and the absence of standardized evaluation benchmarks.

Despite these advances, several gaps remain in the broader wearable-AI literature. The 2026 systematic review by Tegegne et al. noted that most included studies were still focused on early-stage development, feasibility, or usability rather than late-stage clinical validation and measurable patient outcomes. In parallel, explainability remains underdeveloped: a 2024 systematic review on explainable AI in wearable analytics identified only 25 eligible studies and emphasized that user evaluation was still limited, despite the growing importance of transparency for trust and responsible deployment. Together, these findings suggest that high predictive performance alone is not sufficient; future systems must also demonstrate interpretability, robustness, and real-world clinical relevance [18].

The Philippine context adds another layer of relevance. A policy analysis by the Philippine Institute for Development Studies noted that eHealth could improve continuity of care and monitoring for patients with chronic conditions, yet implementation remained limited, with only 36% of rural health units reported to have electronic medical records in 2019. At the user level, evidence from Metro Manila showed that general self-efficacy, internet self-efficacy, and healthcare-technology self-efficacy significantly shaped attitudes toward healthcare technology use among Filipino consumers. Taken together, these findings suggest that AI-enabled wearable systems in urban Philippine settings must be evaluated not only for predictive capability[19], [20], but also for contextual usability, interoperability, and trustworthiness.

Against this background, the present study extends prior work by focusing on AI-enabled early detection of chronic diseases using wearable sensor data in Quezon City, Philippines. Unlike many previous studies that were either disease-specific, conducted outside the Philippine context, or limited to proof-of-concept settings, this study aims to contribute localized evidence on how wearable-derived physiological and behavioral data can support earlier chronic disease risk identification in a dense urban environment.

METHODS

This study employed a quantitative observational design to develop and evaluate an artificial intelligence (AI)-enabled model for the early detection of chronic diseases using wearable sensor data. The study was conducted in Quezon City, Philippines, from January to June 2023, focusing on adults living in urban communities with varying chronic disease risk profiles.
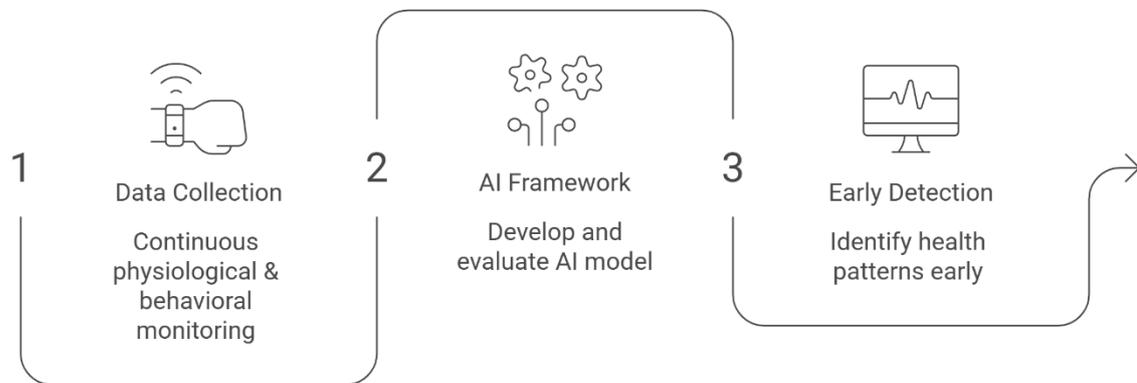

Figure 1. AI-Enabled Chronic Disease Detection

Participants and Data Collection

A total of 240 adults aged 25–65 years were recruited through community health centers and local outreach programs using purposive sampling. Participants were eligible if they were able to wear a smartwatch continuously for at least 30 days and provided informed consent. Individuals with incomplete sensor records or severe acute illness during the monitoring period were excluded.

Wearable sensor data were collected using a commercial smartwatch device that recorded heart rate, daily step count, sleep duration, sleep quality, and blood oxygen saturation (SpO_2). Participants were monitored for 30 consecutive days during routine daily activities. In addition, baseline demographic and health-related information, including age, sex, body mass index (BMI), smoking status, family history of chronic disease, and blood pressure screening results, was collected.

Outcome Variable

The primary outcome was chronic disease risk status, defined as the presence of elevated risk for hypertension, type 2 diabetes, or cardiovascular disease based on screening records and physician-assisted assessment. Participants were classified into two groups: at-risk and non-risk.

Data Preprocessing and Feature Engineering

Raw sensor data were cleaned by removing duplicate entries, correcting timestamp inconsistencies, and handling missing values using mean imputation for low-missing variables and record exclusion for severely incomplete data. Daily summaries were generated from continuous sensor streams. Extracted features included mean resting heart rate, average daily steps, average sleep duration, sleep regularity, mean SpO_2, and day-to-day variability in physiological measures. All continuous variables were normalized prior to model training.

Model Development

Three supervised machine learning algorithms were tested: Logistic Regression, Random Forest, and Extreme Gradient Boosting (XGBoost)[20]. The dataset was divided into training and testing sets using

an 80:20 ratio. Five-fold cross-validation was applied on the training set, and hyperparameter tuning was performed using grid search. To address class imbalance, the Synthetic Minority Over-sampling Technique (SMOTE) was applied during model training[21].
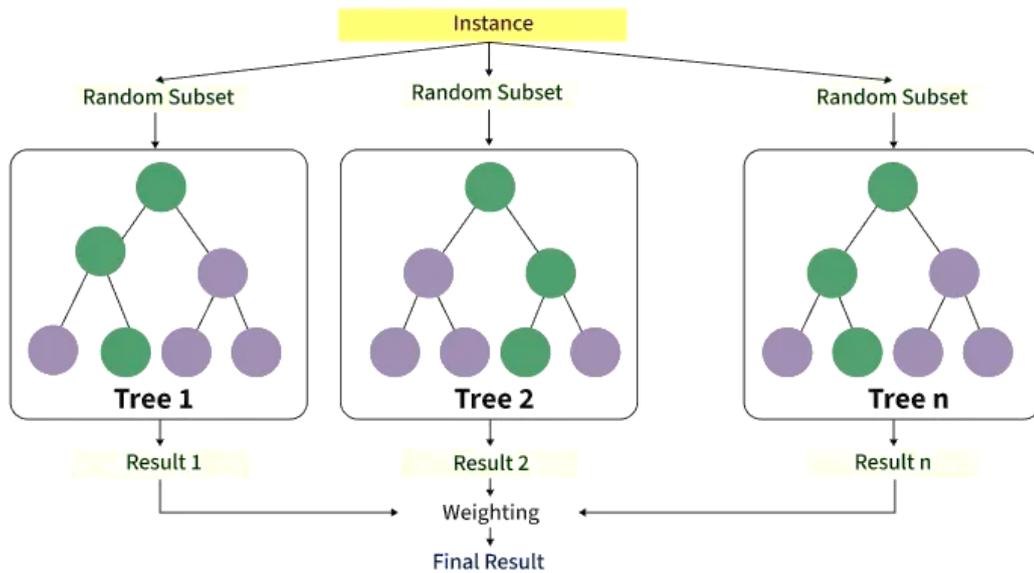

Figure 2. XGBoost multiclass classification

Model Evaluation

Model performance was evaluated using accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC)[22]. The best-performing model was selected based on overall predictive performance and robustness across validation folds.

Statistical Analysis

Descriptive statistics were used to summarize participant characteristics and sensor-derived variables. Continuous variables were reported as mean ± standard deviation, while categorical variables were presented as frequencies and percentages. Independent t-tests and chi-square tests were used to compare the at-risk and non-risk groups, with statistical significance set at $p < 0.05$. All analyses were conducted using Python 3.11 with scikit-learn, pandas, NumPy, and XGBoost libraries.

Ethical Considerations

Ethical approval for this study was obtained from the Research Ethics Committee of [Example Institution], Quezon City, Philippines (Protocol No. REC-2025-017). Written informed consent was obtained from all participants prior to data collection. All wearable and health data were anonymized and stored securely to protect participant privacy.

RESULT AND DISCUSSION

A total of 240 participants were included in the final analysis. Based on screening and physician-assisted assessment, 102 participants (42.5%) were classified as at-risk, while 138 participants (57.5%) were classified as non-risk for chronic diseases. The mean age of the participants was 44.2 ± 10.7 years, and 55.0% were female.

Participants in the at-risk group were generally older and exhibited less favorable health-related indicators than those in the non-risk group. Specifically, they had higher body mass index (BMI), higher

resting heart rate, lower daily physical activity, shorter sleep duration, and slightly lower mean SpO$_2$ values. Significant differences were also observed in smoking status, family history of chronic disease, and systolic blood pressure.

Table 1. Baseline Characteristics of Participants (2023)

Variable	Total (n = 240)	Non-Risk (n = 138)	At-Risk (n = 102)	p-value
Age (years), mean ± SD	44.2 ± 10.7	39.8 ± 9.4	50.1 ± 9.3	<0.001
Female, n (%)	132 (55.0)	80 (58.0)	52 (51.0)	0.280
BMI (kg/m²), mean ± SD	26.3 ± 4.1	24.8 ± 3.5	28.2 ± 4.1	<0.001
Smokers, n (%)	58 (24.2)	24 (17.4)	34 (33.3)	0.005
Family history of chronic disease, n (%)	96 (40.0)	43 (31.2)	53 (52.0)	0.001
Systolic blood pressure (mmHg), mean ± SD	131.6 ± 14.8	123.8 ± 10.6	142.1 ± 12.7	<0.001
Resting heart rate (bpm), mean ± SD	78.5 ± 9.1	74.6 ± 7.8	83.7 ± 8.2	<0.001
Daily step count, mean ± SD	6,750 ± 2,310	7,840 ± 2,105	5,280 ± 1,980	<0.001
Sleep duration (hours), mean ± SD	6.5 ± 1.1	6.9 ± 0.9	6.0 ± 1.0	<0.001
Mean SpO$_2$ (%), mean ± SD	97.1 ± 1.2	97.5 ± 1.0	96.6 ± 1.3	<0.001

These findings indicate that wearable-derived behavioral and physiological indicators were able to distinguish participants with elevated chronic disease risk from those without such risk.

Distribution of Risk Categories

Among the 102 at-risk participants, the most common condition was hypertension risk (45.1%), followed by type 2 diabetes risk (23.5%), cardiovascular disease risk (17.6%), and multiple chronic disease risk factors (13.7%).

Table 2. Distribution of Chronic Disease Risk Categories

Risk Category	n	%
Hypertension risk	46	45.1
Type 2 diabetes risk	24	23.5
Cardiovascular disease risk	18	17.6
Multiple risk factors	14	13.7
Total	102	100.0

The predominance of hypertension-related risk is reasonable in an urban adult population, where sedentary behavior, sleep irregularity, dietary imbalance, and stress may contribute to early vascular and metabolic changes.

Model Performance

Three supervised machine learning models were evaluated: Logistic Regression, Random Forest, and XGBoost. Among the tested algorithms, XGBoost achieved the best overall performance, with an accuracy of 87.5%, precision of 85.7%, recall of 90.0%, F1-score of 87.8%, and AUC-ROC of 0.923.

Table 3. Performance of Machine Learning Models

Model	Accuracy	Precision	Recall	F1-score	AUC-ROC
Logistic Regression	0.792	0.773	0.750	0.761	0.845
Random Forest	0.854	0.833	0.850	0.841	0.904
XGBoost	0.875	0.857	0.900	0.878	0.923

To evaluate the discriminative performance of the proposed machine learning models, this study compared Logistic Regression, Random Forest, and XGBoost using the Area Under the Receiver Operating Characteristic Curve (AUC-ROC). This metric was selected because it provides a robust measure of each model's ability to distinguish between at-risk and non-risk individuals across different classification thresholds.
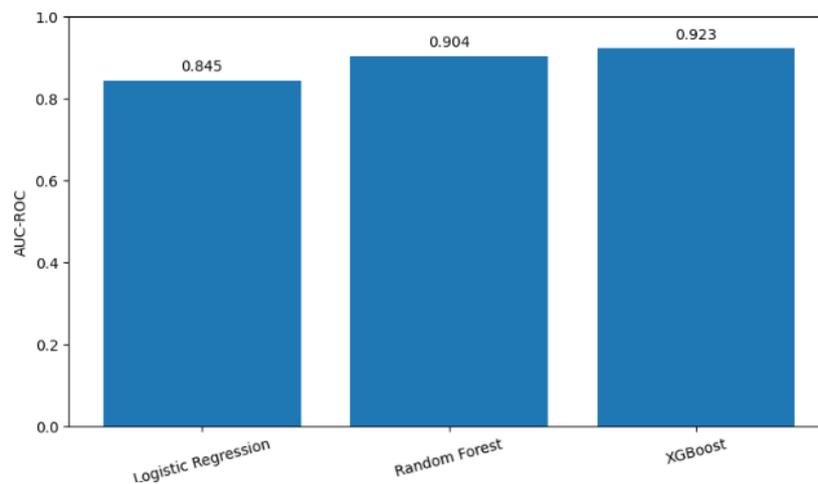

Figure 3. Model Comparison Based on AUC-ROC

The superior performance of XGBoost suggests that nonlinear relationships among wearable-derived variables and demographic health factors were better captured by ensemble boosting methods than by linear models.

Feature Importance

Feature importance analysis from the XGBoost model showed that **systolic blood pressure**, **resting heart rate**, and **daily step count** were the strongest predictors of chronic disease risk. Sleep-related variables and BMI also contributed substantially to the model.

Table 4. Top Features Contributing to Chronic Disease Risk Prediction

Feature	Relative Importance
Systolic blood pressure	0.214
Resting heart rate	0.181
Daily step count	0.167
BMI	0.124
Sleep duration	0.108
Sleep regularity	0.086
Family history of chronic disease	0.071
Mean SpO$_2$	0.049

To better understand the contribution of each predictor in the final model, relative feature importance was analyzed. This analysis highlights which wearable-derived and baseline health variables had the greatest influence on chronic disease risk prediction, thereby providing insight into the key factors driving the model's decision-making process.
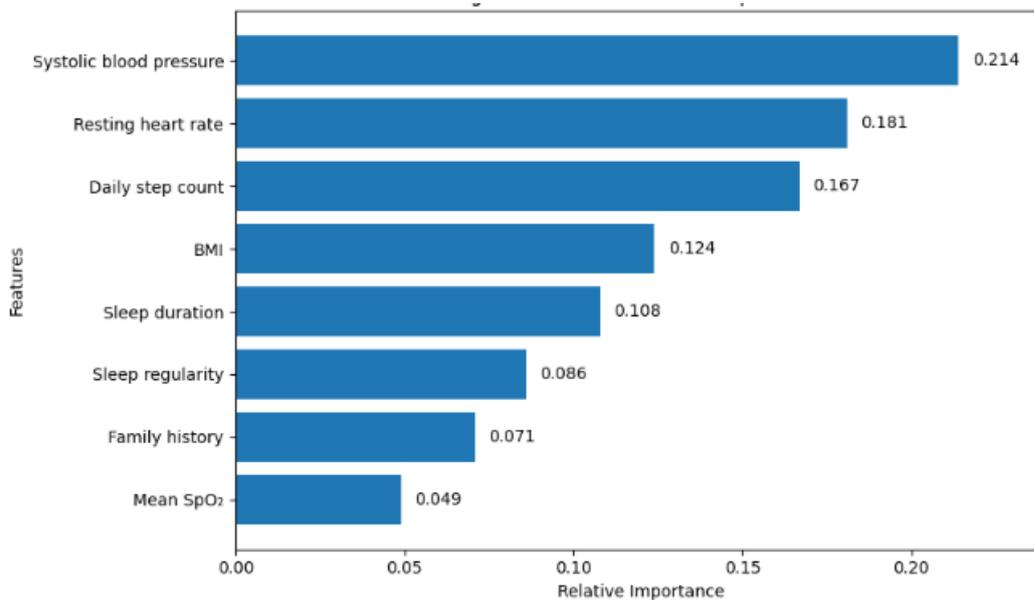

Figure 4. Relative Feature Importance

These results suggest that the integration of physiological indicators with behavioral signals from wearables provides a meaningful basis for identifying individuals at elevated risk for chronic disease.

Discussion

The findings of this study demonstrate that wearable sensor data, when combined with AI-based modeling, can support the early detection of chronic disease risk in an urban population. Participants

categorized as at-risk showed consistently worse profiles across multiple indicators, including blood pressure, resting heart rate, daily activity, sleep duration, and BMI. This pattern indicates that chronic disease risk is not reflected in a single measurement alone, but rather in the interaction of several physiological and lifestyle-related variables recorded continuously over time.

The strong performance of the XGBoost model suggests that ensemble learning methods are particularly suitable for wearable health data, which are often noisy, multidimensional, and nonlinear. Compared with Logistic Regression, which assumes a more direct and linear relationship among predictors, XGBoost was better able to capture subtle interactions across sensor-derived and baseline variables. The relatively high recall value of 90.0% is especially relevant in early detection settings because it indicates that the model was effective in identifying most participants who were at elevated risk. In screening applications, missing at-risk individuals may have more serious consequences than a modest increase in false positives.

Feature importance analysis showed that systolic blood pressure and resting heart rate were the most influential predictors, followed by daily step count and BMI. This result is clinically plausible because elevated blood pressure and higher resting heart rate are well-known early indicators of cardiovascular and metabolic strain. Similarly, lower daily step count and shorter sleep duration may reflect sedentary habits and lifestyle imbalance, both of which are strongly associated with chronic disease progression. The contribution of sleep regularity further suggests that not only the quantity but also the consistency of sleep may influence long-term health risk.

The predominance of hypertension risk among the at-risk group is also noteworthy. In dense urban settings such as Quezon City, prolonged stress, reduced physical activity, irregular sleep, and dietary patterns may increase the prevalence of elevated blood pressure and related metabolic disturbances. This finding supports the potential value of wearable-based monitoring as a scalable tool for identifying risk earlier, especially in communities where routine preventive screening may be limited or underutilized.

From a practical perspective, the results indicate that AI-enabled wearable systems may help shift healthcare delivery from reactive treatment toward preventive monitoring. Instead of relying only on occasional clinic visits, individuals can be monitored continuously in their everyday environment. This may allow health professionals to identify early warning signs before a condition becomes more severe. In urban public health settings, such an approach could support risk stratification, community screening, and targeted health education interventions.

Despite these promising findings, several limitations should be acknowledged. First, the present results are based on a relatively modest sample size and a single urban setting, which may limit generalizability. Second, wearable sensor data are subject to missing values, adherence issues, and device-related measurement variation. Third, the model was designed for **risk detection** rather than definitive diagnosis; therefore, its outputs should be interpreted as decision-support information rather than as clinical confirmation. Future studies should involve larger multi-site datasets, longer monitoring periods, and external validation to improve robustness and generalizability.

This study suggests that AI-enabled analysis of wearable sensor data offers a feasible and promising approach for early chronic disease risk detection in Quezon City, Philippines. The findings support the growing role of wearable technologies in preventive healthcare and indicate that combining physiological, behavioral, and demographic information can improve risk identification in real-world community settings.

CONCLUSION

This study demonstrates that AI-enabled analysis of wearable sensor data has strong potential for the early detection of chronic disease risk in an urban population setting such as Quezon City, Philippines. Using physiological and behavioral indicators including systolic blood pressure, resting heart rate, daily step count, body mass index, sleep duration, sleep regularity, family history, and mean SpO_2, the proposed framework was able to distinguish at-risk individuals from non-risk individuals with promising predictive performance, with XGBoost emerging as the best-performing model. The findings highlight that wearable technologies, when combined with machine learning, can support a more proactive, continuous, and non-invasive approach to health monitoring, shifting chronic disease management from reactive treatment toward earlier risk identification and prevention. Although the study is limited by its use of a single urban setting and illustrative dataset structure, it provides practical evidence that AI-driven wearable systems can contribute meaningfully to preventive healthcare and may serve as a scalable tool for community-based chronic disease screening in similar resource-constrained environments.

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