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Multimodal Omics and Wearable Sensor Data Fusion for Continuous Cardiometabolic Health Assessment

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ABSTRACT

Background: Diabetes, hypertension, and cardiovascular diseases are cardiometabolic diseases that are the major causes of morbidity and mortality globally. Conventional approaches to health monitoring are not very sensitive to the dynamic nature of these states, which is why continuous, real-time health measurements are required. Objectives: The proposed research endeavors to incorporate multimodal omics data (genomic, proteomic, and metabolomic) with wearable sensor data for continuous cardiometabolic health monitoring and to construct a predictive model to evaluate cardiometabolic risk using a combination of these varied data sets. Materials and Methods: The genomic, proteomic, and metabolomic data were obtained among 150 participants with different cardiometabolic risks, who were wearing smartwatches and continuous glucose monitors to measure their heart rate, blood pressure, and glucose level. Preprocessing was done on the data, and machine learning models, including deep learning models, were employed to combine data and predict risks. Results: The predictive model had an accuracy of 85% and an AUC-ROC of 0.92, which is significantly higher than that of traditional clinical measures (70% accuracy; AUC-ROC = 0.76). This model showed great predictive capacity regarding the integration of omics with sensor data to better predict cardiometabolic risk. Conclusion: The paper provides evidence of the opportunities in the combination of omics data and wearable sensors to enable continuous and personalized cardiometabolic health monitoring, achieving a path to precision medicine and preventive disease treatment.

Keywords: *Multimodal Omics, Wearable Sensors, Cardiometabolic Health, Real-time Monitoring, Data Fusion, Personalized Medicine, Machine Learning.*

INTRODUCTION

One of the major causes of morbidity and mortality in the world is cardiometabolic diseases, which include diabetes, hypertension, and cardiovascular diseases (CVD). The World Health Organization (WHO) reports 17.9 million people die every year of cardiovascular diseases, and 1.6 million of them die of diabetes [6]. The rising cases of the conditions have led to the creation of more efficient diagnostic instruments, treatment approaches, and preventive mechanisms. Conventional approaches to the evaluation of cardiometabolic health rely largely on clinical indicators and infrequent screenings, and in many cases do not reflect the dynamic and changing nature of these diseases. The recent years have seen the increasing interest in the

adoption of new advanced technologies, including wearable sensors and omics data, to deliver start-to-stop and personalized health assessments [1]. This would transform cardiometabolic disorder treatment and prevention since it provides real-time information on the health condition of an individual.

The emergence of wearable sensors has tremendously increased health monitoring opportunities [2]. Smartwatches and other fitness watches can continuously measure a variety of physiological variables, including heart rate, blood pressure, physical activity, and glucose levels. These sensors are invaluable in monitoring the changes in the health of an individual since they allow real-time, non-invasive monitoring. Nevertheless, wearable sensors give a shallow insight since they primarily record the surface type of information without getting into the molecular or cellular mechanisms underlying cardiometabolic diseases [3].

Omics technologies, on the other hand, like genomics, proteomics, and metabolomics, are so insightful about the molecular processes by which the disease progresses [10]. Genomic data could be used to give genetic predispositions to diseases, whereas proteomic and metabolomic data would give us an insight into the biochemical processes and the physiological processes of the body [8]. These technologies have been effective in the discovery of biomarkers of most health conditions, such as cardiometabolic diseases [9]. Nevertheless, they have not yet received clinical use in practice because the data is complex and high-dimensional, which is complicated by the difficulty of their integration with real-time physiological monitoring. The most recent developments in data fusion methods have given rise to multimodal approaches, which integrate the data produced by wearable sensors with omics data, which promise an opportunity to have a more holistic and comprehensive understanding of the health of a particular person [4][5]. It is this combination of these various sources of data that can help close the divide between molecular knowledge and the actual health outcomes in the real world and deliver a more accurate and timely measurement of cardiometabolic health.

The proposed research is expected to create a framework of continuous cardiometabolic health analysis through combining the multimodal omics information with wearable sensor information that will provide real-time, personalized information [7]. The integration has the potential to help enable early identification, better risk stratification, and more efficient interventions of cardiometabolic illnesses. The strategy provides real-time tracking, discovery of diseases at early stages, and discovery of new biomarkers to use in precision medicine. Nonetheless, the issues of working with large amounts of data and the privacy concerns can be regarded as challenges. These challenges will be overcome by the study, developing a data fusion model to integrate wearable sensor and omics data, which will improve diagnostics and personalization of treatment.

Key Contributions:

1. Combination of the genomic, proteomic, and metabolomic data with wearable sensors in real-time continuous monitoring of cardiometabolic health.
2. The fused data predictive model was found to give 85 %accuracy and an AUC-ROC of 0.92, which was higher than the conventional clinical assessments.
3. Shown the potential of precision medicine in the initial disease detection and treatment, data integration, and privacy issues.

This article is organized in the following way: The Abstract will provide the goals of the research, methods, results, and conclusions with references to the combination of omics and wearable sensors data in the continuous cardiometabolic health monitoring. The Introduction has given an overview of the importance of cardiometabolic diseases and presents the new strategy. The Data collection and fusion are described in Materials and Methods. Results are findings of the integrated data, and the Discussion explains the results. The Conclusion is the summary of the impact and offers a way for further research.

Materials and Methods

This research involved a multimodal system that incorporated the use of omics data (genomic, proteomic, and metabolomic) and measurements of wearable sensors to constantly monitor cardiometabolic health. Whole blood was used to extract genomic data, plasma and serum were used to extract proteomic and metabolomic data, respectively, by mass spectrometry. To follow the physiological parameters (heart rate, activity, glucose, and blood oxygen), participants were provided with wearable devices such as smartwatches and continuous glucose monitors. Real-time collection of data over a six-month period and preprocessing of omics and sensor data in real-time have been conducted. Deep learning algorithms that were predictive and assessed cardiometabolic health conditions were applied using machine learning algorithms.

2.1 Study Population and Design

The study design was a cohort longitudinal study and observational. A total of 150 participants aged between 18 and 65 years were recruited in a community health center, and therefore, a diversified sample of the subjects at various risks of cardio metabolism was attained. Inclusion criteria were that the individuals had already been diagnosed or were at risk of getting hypertension, whereas the exclusion criteria were based on the fact that they were severely ill, such as with cancer or severe infections. The respondents were required to sign the informed consent, and all the procedures were to be approved by the ethics committee.

2.2 Sample Collection

In the first stages of the study and six months of constant observations, genomic, proteomic, and metabolomic samples of blood were taken. The standard extraction kits were used in extracting the genomic DNA from whole blood, and the plasma and serum samples collected during fasting were analyzed using the proteomic and metabolomic techniques. The respondents were provided with wearable sensors at the onset of the research, and the data were monitored and transmitted to a cloud platform to process the data. The participants were also informed on how to use and wear the sensors in order to have accurate data. Periodic follow-ups were conducted to ascertain that the study protocol was being followed, and additional data concerning lifestyle-related issues, e.g., diet and physical activity, were obtained at regular intervals by use of self-reported questionnaires.

2.3 Biochemical analysis

In the current context of the paper, biochemical analyses may be referred to as analysis of biological substances (blood, plasma, serum, or tissue) to gain an understanding of the correlative molecular and metabolic changes of cardiometabolic diseases. Biochemical analyses that were of importance in the given study are:

Genomic Analysis: The genomic analysis involves examination of the DNA of an individual to determine genetic variations like single-nucleotide polymorphisms (SNPs) or mutations that can potentially predispose a person to cardiometabolic diseases. DNA is sequenced by using such techniques as next-generation sequencing (NGS) to discover genetic factors that can guide cardiovascular health, blood sugar regulation, and lipid metabolism. The discovery of these genetic markers assists scientists in determining the genetic risk factors of specific diseases like diabetes, high blood pressure, and heart disease to identify early, as well as know the level of risk.

Proteomic Analysis: The proteomic analysis is used to study proteins in such samples of the body as plasma or serum and to determine which ones are related to inflammation, lipid metabolism, and insulin resistance. Protein expression levels are detected and measured using such techniques as liquid chromatography-tandem mass spectrometry (LC-MS/MS). This may assist researchers in identifying biomarkers in

cardiometabolic diseases and also understanding the processes in the biochemistry and cellular processes that contribute to these diseases, which will contribute to the monitoring and progression of these diseases.

Metabolomic Analysis: Metabolomic analysis involves looking at the metabolites (small molecules) in the biological samples to determine how the body works. Measurement of metabolites in energy metabolism, lipid metabolism, and regulation of glucose is done using techniques such as gas chromatography-mass spectrometry (GC-MS) and liquid chromatography-mass spectrometry (LC-MS). Through metabolite profile changes, scientists will be able to identify the initial indicators of metabolic imbalance, a symptom of cardiometabolic disorders, including diabetes and heart disease, and identify the disrupted metabolic pathways and the biomarkers.

Data Analysis of Wearable Sensors: Wearable sensor data were constantly measured through the use of devices such as smartwatches and glucose monitors, including heart rate, blood pressure, physical activity, and glucose. Preprocessing of the data was done to eliminate noise and matched to omics data. The main measures were summarized by descriptive statistics, and machine learning, including the use of deep learning algorithms, was applied to discover patterns and trends in the sensor data that were related to cardiometabolic health changes. This discussion was able to establish how sensor data predicts early signs of cardiometabolic diseases.

Results

3.1 Genomic Analysis

Using the genomic analysis, the identification of important single-nucleotide polymorphisms (SNPs) linked to cardiometabolic diseases was made. The APOE gene SNP results were significantly linked to high levels of LDL cholesterol ($p = 0.03$), and FTO gene variants were highly linked with high BMI ($p < 0.001$) among individuals with a high-risk cardio metabolite. The genetic markers shed some light on genetic predispositions that contribute to lipid metabolism and body weight regulation, which are critical determinants of cardiometabolic health.

3.2 Proteomic Analysis

Proteomics showed that the patients with greater cardiometabolic risk had increased C-reactive protein (CRP) (mean increase of 1.2 mg/L, $p = 0.02$) and adiponectin (mean increase of 7.5 µg/mL, $p = 0.01$), which are indicators of increased inflammation and insulin resistance, respectively. On the other hand, there was a great reduction in the level of fibronectin in high-risk subjects (average reduction of 5.4 ng/ mL, $p = .04$), indicating dysfunction on the endothelial side. The presence of these protein markers is evidence of the inflammatory and metabolic processes that cause cardiometabolic diseases.

3.3 Metabolomic Analysis

The LC-MS/MS method of metabolomic profiling detected significant metabolites that differed between low- and high-risk patients. The level of palmitic acids increased considerably in high-risk people (mean upsurge of 12%, $p = 0.005$), and glucose-related metabolites, such as lactate and pyruvate, were significantly upsurged in level in people with compromised glucose regulation ($p = 0.003$). The metabolic changes are indicative of dysregulation in lipid and glucose metabolism, which are both typically disturbed in cardiometabolic diseases like diabetes and heart disease.

3.4 Wearable Sensor Data

Smartwatch and continuous glucose sensor data, such as wearable sensor data, were taken that showed heart rate variability (HRV) and blood glucose levels. High-risk individuals demonstrated a significant reduction in HRV, and the mean reduction was 18 % ($p = 0.02$), and this was correlated with high levels of CRP, indicating dysfunction in autonomic activity. The variation in glucose levels was more significant among

the participants at the highest risk, and the mean level of glucose variability was 15% ($p = 0.01$), which was again linked to the metabolomic results of disrupted glucose regulation. These physiological variations are an added testimony of the dysfunctional metabolism of people at a greater risk of cardiometabolic diseases.

3.5 Machine Learning Model Performance

A combination of genomic, proteomic, metabolomic, and wearable sensor measurements to machine learning models was found to predict cardiometabolic risk with an accuracy of 85% (AUC-ROC = 0.92) compared to traditional clinical measurements of the same risk, which had an accuracy of 70% (AUC-ROC = 0.76). The machine learning models established the possibility of combining all these various data sources to enhance early detection, risk stratification, and individualized health monitoring of cardiometabolic diseases.

Discussion

This study has proven that continuous, personalized cardiometabolic health monitoring has considerable potential because of the integration of multimodal omics data and wearable sensor data. According to our genomic analysis, found significant variants of the APOE and the FTO genes that play a decisive role in lipid metabolism and obesity, which is the central focus of cardiometabolic risk. The findings are in line with the previous studies and reveal the genetic nature of predisposition to such diseases as hypertension and diabetes. Also, the proteomic analysis demonstrated high concentrations of C-reactive protein (CRP) and adiponectin among the high-risk people, which once again proves the importance of inflammation and insulin resistance in the development of the disease. The results not only support the genomic evidence but also give biomarkers to track the disease movement and guide the treatment options.

This was also supported by the metabolomic analysis that found a major dysregulation in glucose and lipid metabolism. High levels of palmitic acids and impairment of glucose-derived metabolites, including lactate, were manifested in high-risk patients, which indicated that the body lacked the ability to control metabolic activities. These results highlight the potential of metabolomics to act as a first line of disease markers, so that it can detect disease early enough before clinical manifestations occur. The wearable sensor data that offered real-time values of heart rate, blood pressure, and glucose levels had a close correlation with omics data, which added to the overall image of cardiometabolic health. The reduction in the heart rate variability (HRV), especially in at-risk patients, indicates dysautonomia activity related to cardiovascular risk and the importance of continuous physiological monitoring. More so, the analysis of omics and sensor data into a predictive model yielded 85% accuracy and an AUC-ROC of 0.92, which was better than the traditional methods. Future opportunities and threats encompass the refinement of the model to be used on a wider application and data security, which leads to the necessity of conducting more studies in data integration and privacy protection. This research proves the possibility of using omics and wearable sensor data together to improve the level of cardiometabolic health evaluation and intervention in individuals.

Conclusion

The present research shows that multimodal omics data, combined with wearable sensor technology, have great potential to be used to continuously monitor cardiometabolic health. With the integration of genomic, proteomic, and metabolomic data and real-time physiological indicators of wearable sensors, a notion of a multifaceted and individualized system of health assessment was created, which considerably enhanced the detection of early disease, the stratification of risks, and the development of an intervention approach. The models that were predicted based on this data fusion had high accuracy with 85 % success rate and an AUC-ROC of 0.92, as compared to the conventional methods of monitoring. These findings are encouraging, but there is still work to do, especially on how to increase the generalizability of the machine learning models to different populations and risk profiles. It is also important to address privacy and security issues of sensitive health information, particularly when personal genetic information is combined with constant

sensor data. Also, the model has shown effectiveness in a controlled cohort, but its applicability to practice requires more large and diverse studies. The researchers should work on developing the model in the future by adding more health parameters to it, like mental health indicators and environmental factors, to give a more comprehensive picture of health. Improving the practical application of the system by individuals and healthcare providers will also require the improvement of data integration algorithms, real-time analytics, and user-friendly interfaces, as well. Finally, this study enables a proactive, precision-oriented management and prevention of cardiometabolic diseases with the help of continuous, real-time health monitoring and individual interventions.

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