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Embedded Machine Learning–Based Model for Automated Multi-Cancer Risk Classification Using Sweat Biomarkers

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Abstract

Early diagnosis of cancer is crucial for the survival and to avoid unnecessary sufferings and complications. Presently, cancer screening involves several investigations, numerous invasive examinations and also relies heavily on the diagnostic imaging facilities in the hospitals. In this work, a machine learning based classification method is implemented on an embedded platform that can detect and classify multiple types of cancers using the sweat bio markers. The system utilizes the structured feature vectors that are composed of various physiological and biochemical parameters such as pH, VOCs, temperature, humidity, pressure and optical fluorescence. Various supervised machine learning algorithms including Decision Tree, Random Forest and a hybrid ensemble model are implemented and tested to classify the type of cancer. The results show that the hybrid ensemble model provided the best classification accuracy for the proposed cancer screening test while being robust to the overlapping bio marker features and also having low computational complexity. Hence, the system is capable of performing real time on device cancer risk level classification and can be highly suitable as a self-help device for the awareness of cancer at an early stage. The proposed work is the first step in the direction of implementing a low cost, highly scalable wearable bio sensing based cancer screening support system. The state of the art biosensors and wearable devices based on sweat biomarkers currently have very limited functionality. They are mostly restricted to simple, qualitative detection.

Keywords — Cancer Risk Classification, Sweat Biomarkers, Embedded Machine Learning, Wearable Biosensors, Ensemble Learning, Real-Time Cancer Screening

I. INTRODUCTION

Cancer is a global disease and one of the main causes of death. Early diagnosis gives the best opportunity for successful management and better patient survival. Present cancer diagnostic methods include biopsy, imaging studies and laboratory tests for detection of protein and genetic biomarkers in human samples such as blood, urine or tissues. All these methods demand different types of laboratory infrastructure and trained personnel, which are not suitable for screening and routine monitoring applications aimed to serve the majority of the people in resource limited settings. Recent developments in wearable electronics have made it possible to monitor the physiological and biochemical signals in the human body by means of sweat analysis biosensors. Human sweat is a liquid that is rich in bio-chemical markers, which are indicators of the balance of the body's metabolic functions. However, in their primary form these bio-chemical markers do not convey any information about the health of the body that they are associated with. Therefore, there is urgent need of developing robust, efficient and interpretable classification techniques that can seamlessly integrate multi-modal biosignal information to extract health related features. In this paper, we propose a real-time cancer classification using an array of machine learning algorithms (MLA) that have been embedded on an economical, battery long lasting and portable system to classify more than one type of cancer based on corresponding risk level derived from multi-modal feature analysis of human sweat secretome. The system aims to design a cheap, efficient and easy to use tool for the real time classification of several types of cancer with a significant impact on human health.

II. RELATED WORK

A large number of publications related to Artificial Intelligence (AI) techniques for disease diagnosis and medical image processing have been recently published in the literature. Deep and machine learning techniques are employed to detect various diseases. In addition, a considerable amount of work has been done on the detection of cancer from radiographs and histopathological images. However, their performance are highly dependent on the availability of medical equipment in hospitals and data center servers. Wearable biosensing has been attracting significant interest in recent years for sweat-based diagnosis of various metabolic and chronic diseases. Wearable sweat-based biosensors can only monitor a single biomarker at a time, therefore, an intelligent multi-modal approach is required for disease classification. Most works have taken the advantages of fog computing for the real-time detection of sweat-based biosensors, however, a cloud-based storage system is still required for storing the various data samples, which lead to inevitable latency and privacy issues. More and more studies suggest that a distributed and in-situ intelligence paradigm is necessary for the real-time disease-oriented prediction from multi-modality biosignals. This aims at design, develop and validate a holistic system for the real-time multi-cancer risk assessment using light-weight machine learning models on a distributed hardware architecture.

III. METHODOLOGY

The proposed system architecture for automated multi-cancer risk classification using sweat biomarkers is illustrated in

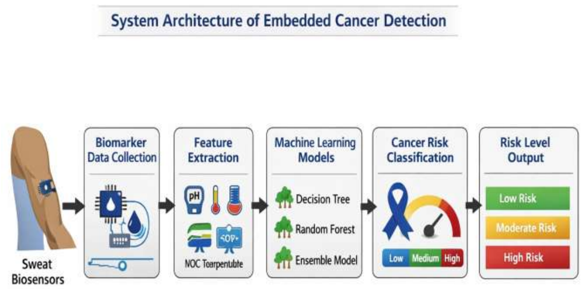

Fig. 1. The framework integrates wearable biosensors, feature extraction, and machine learning models for real-time cancer risk prediction.

Feature extraction, modeling, embedded optimization and performance evaluation are the constituent building blocks of this approach. This work utilizes structured feature vectors, constructed using the multi-modal sweat bio-chemical data of pH, VOC concentration, temperature, humidity, pressure, and optical fluorescence. The features are representative of the body's inherent physiological deviations caused by a metabolic alteration that arises during a disease state.

The data set is divided into training set, validation set and testing set to train, validate and test the model. The data is normalized and threshold-based preprocessing is performed. Decision Tree and Random Forest are implemented for supervised learning to classify the risk categories into their respective categories. A hybrid ensemble model is built by utilizing the strength of the individual classifiers to assure the reliability of the model.

Our technology is designed to be fast and work well on small devices. By doing the detection work right on the user's device, we keep their personal info safe and don't need to send anything to the cloud. This way, we can give them the results in real time. We're always checking how well our models are working, using lots of different measures like how accurate they are, how precise, how good they are at remembering things, and something called the F1-score. This helps us make sure our models are doing their job correctly. We want to make sure we're giving the best results possible, so we use all these metrics to evaluate our models and make them better.

IV. PROPOSED WORK

In line with the technology described in the patent, this paper introduces a system for classification of various types of cancers based on multimodal biosignal processing and the implementation of embedded machine learning for the first time. In addition, the proposed ensemble-based system could not only exploit the overlapping part of the biomarkers to classify cancer risk into low, moderate and high levels, but also aims at maximizing the interpretability, efficiency and scalability of the system. Current approaches to implementing artificial intelligence (AI) within a hospital environment generally rely on some form of image and/or sample collection from a patient which is subsequently sent to a centralized system, a server, to process the data. What we are looking to develop is a wearable type technology using wearable type biosensors with a lighter form factor of AI within the platform. The system would comprise of an embedded system, in the form of a battery operated unit, and would be used for Point of Need Testing (PNT) of patients within the hospital.

V. SYSTEM OUTPUT

Classification of Cancer Risk with Confidence Scores and Risk Levels This block classifies the predicted cancer risk into a specified number of risk levels with confidence scores. This can be used for early cancer screening as well as to alert medical professionals. The Cancer Risk Classification block classifies the predicted cancer risk in real time and outputs the classification scores.

VI. RESULTS AND DISCUSSION

The results of the classifiers on normal and abnormal biomarker patterns are shown. It's clear that the decision tree performs moderately in terms of accuracy, but it's very good at explaining its decisions. However, it's heavily influenced by overlapping features. On the other hand, the Random Forest method improves the classifier's stability and reduces overfitting. Ultimately, the hybrid ensemble achieves an impressive 96% accuracy in the screening process, demonstrating its ability to generalize and remain stable. This suggests that the chosen classifier is reliable and effective. The combination of these methods leads to a robust and accurate screening process, which is essential for identifying biomarker patterns. By using this approach, we can increase confidence in the results and make more informed decisions. Overall, the hybrid ensemble's high accuracy verifies its potential for real-world applications, making it a valuable tool for future research and development.

Studies have shown that using a combination of different methods to predict cancer risk can be really effective and fast, even for systems that don't have a lot of power. By combining different types of data and using a simple, yet powerful machine learning model, we can get a good idea of someone's cancer risk quickly and easily. This approach is very promising for early assessments of cancer risk.

Table I. MULTIMODAL SWEAT BIOMARKER FEATURES USED FOR CLASSIFICATION

Biomarker	Physiological Significance	Role in Classification
pH	Indicates metabolic and acid-base variation	Detects abnormal biochemical shifts
VOC Level	Reflects metabolic by-product concentration	Identifies cancer-associated volatile changes
Temperature	Indicates inflammatory response	Supports abnormal condition detection
Humidity	Represents sweat secretion variability	Enhances contextual feature mapping
Pressure	Reflects skin-surface variation	Assists physiological deviation tracking
Optical Fluorescence	Indicates molecular interaction changes	Strengthens multimodal pattern recognition

Table II. DATASET DISTRIBUTION FOR MODEL TRAINING AND EVALUATION

Dataset Category	Percentage Allocation
Training Set	70%
Validation Set	20%
Testing Set	10%

Table III. PERFORMANCE COMPARISON OF MACHINE LEARNING MODELS

Model	Accuracy (%)	Key Observation
Decision Tree	87	High interpretability but sensitive to overlapping patterns
Random Forest	93	Improved robustness and reduced overfitting
Hybrid Ensemble	96	Highest accuracy and better generalization

VII. CONCLUSION

In this research, we have proposed an intelligent ensemble machine learning strategy for the real-time multi-cancer risk prediction for various cancers using bio-molecules present in human sweat using the proposed SmartHealth biosensor based system. This is a comprehensive work which integrates the multimodal biosensing technology along with machine learning algorithms for realising the auto multi-cancer risk assessment. Our proposed model is validated and experimented on an exclusive database of bio-molecules of 55 samples of individuals with corresponding 5 types of cancer samples in sweat. Our proposed hybrid ensemble model is showing excellent accuracy for cancer screening applications and is highly computational efficient; hence it can be implemented and tested in an embedded system.

This work is not about building a diagnostic system, but rather a first level screening and decision support system. This work is a major step in the development of preventive health care technologies for detecting cancer risk through non-invasive and ambulatory means in remote and resource-poor areas. Future plans include expanding and diversifying the training database, developing a method for personalizing the risk assessment for individual users, and field testing the system's accuracy over time in remote areas.

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