Wearable Sensors and Machine Learning: Insights into Depression, Anxiety, and Emotional States and Changes

Wei Zhao[1]
[1]*Interdisciplinary Graduate School of Medicine and Engineering University of Yamanashi*
Kofu 4008511 Japan
g22dtsa4@yamanashi.ac.jp

Kentaro Go[2]
[2]*Interdisciplinary Graduate School University of Yamanashi*
Kofu 4008511 Japan
go@yamanashi.ac.jp

***Abstract*—Mental health disorders, such as depression and anxiety, significantly impact individuals worldwide, yet timely diagnosis and intervention remain challenging due to the subjective nature of traditional methods. Wearable technology, including devices such as smartwatches and smartphones, combined with machine learning, offers new opportunities to monitor and predict mental health conditions. This paper provides a comprehensive review of studies published between 2013 and 2023, focusing on the application of wearable devices and machine learning to predict emotional states and changes. We summarize commonly used machine learning methods, such as support vector machines and random forests, alongside key features extracted from wearable data, including physiological indicators and behavioral patterns. Unlike previous reviews, this work emphasizes the underexplored area of emotional changes, identifying gaps in current research and proposing future directions. The findings aim to inspire innovative approaches to the monitoring and intervention of mental health.**

***Index Terms*—smartphone, smartwatch, depression, anxiety, emotion, machine learning**

I. Introduction

Mental health disorders, such as depression and anxiety, have a significant impact on the lives of individuals, affecting their ability to work, maintain relationships, and achieve a good quality of life. These disorders are highly prevalent, with one in four people worldwide experiencing anxiety or depression during their lifetime [5]. However, timely diagnosis and intervention remain challenging due to the subjective nature of self-reporting and the lack of clear physiological markers [1]. Traditional diagnostic approaches often suffer from subjectivity to symptoms, emotional and cognitive impacts, and confirmation biases, which further complicate the diagnostic process.

Recent advances in wearable sensor technology, including devices such as smartwatches, smartphones, and fitness trackers, have revolutionized mental health monitoring. These devices enable the continuous and passive collection of rich behavioral and physiological data, such as heart rate, sleep patterns, and physical activity. This has opened new possibilities for applying machine learning to detect, predict, and manage mental health conditions with greater accuracy and timeliness [2], [3]. Despite this potential, current studies often focus on static psychological states, leaving the dynamic nature of emotional changes underexplored.

Emotion detection itself presents several challenges. The data used for emotion detection varies significantly, ranging from physiological signals (e.g., heart rate and skin conductance) to behavioral patterns (e.g., smartphone usage and activity levels) and self-reported measures (e.g., diaries and questionnaires). Each data source has its strengths and limitations: physiological data is objective but often requires specialized devices, behavioral data are more accessible but less precise, and self-reported data are subjective and prone to bias. Furthermore, the settings in which data are collected—controlled laboratory environments versus real-world, unconstrained scenarios—further contribute to variability in results and applicability. Capturing dynamic emotional changes also requires models capable of processing high-temporal-resolution data, which remains a technical challenge. These complexities highlight the need for robust methodologies and diverse datasets to enhance emotion detection research.

This review arises from the rapid growth of wearable technology and its application in mental health studies. While previous reviews have summarized machine learning methods for mental health prediction, most have centered on depression and anxiety as static states rather than exploring emotional changes. This review aims to address this gap by focusing on studies leveraging wearable devices to predict emotional states and their changes.

II. Review Methodology

We conducted a systematic review of the literature published between 2013 and 2023. Keywords were derived from four main categories: devices, mental health symptoms, methodologies, and emotional states and changes. These keywords included terms such as “smartwatch”,“smartphone,” “depression,” “anxiety,” and “machine learning.” Searches were conducted in seven major databases, including Google Scholar, ACM Digital Library, IEEE Xplore, SAGE, ScienceDirect, SpringerLink, and Web of Science.

The search process followed a structured approach, including deduplication, screening, and evaluation. For instance, the search query used in Google Scholar was:

> ("smartphone" OR "smartwatch" OR "wearable device") AND (anxiety OR depression OR emotion OR mental OR mood OR "panic disorder" OR stress) AND "machine learning" AND ("state" OR "change")

Inclusion criteria required studies to employ machine learning to predict emotions, anxiety, or depression, use wearable devices for data collection, and meet minimum quality standards such as sufficient sample sizes and sound study designs. Studies lacking machine learning applications or published before 2013 were excluded. This methodological framework ensures transparency and reproducibility in our review process.

III. Main findings

A. Method

The selected studies utilized various machine learning methods to predict depression, anxiety, and emotional states. These methods can be categorized into three groups: existing methods, hybrid methods, and newly developed methods. Depending on the dataset and evaluation criteria, different machine learning methods performed optimally. Support vector machines (SVM), random forests (RF), and XGBoost are the three most commonly used methods [5], [9]–[11]. In particular, SVM with an RBF kernel has shown high sensitivity in detecting depression, effectively identifying patients with depression [10]. For example, studies by Yue et al. [5], Farhan et al. [9], and Ware et al. [12] reported F1 scores as high as 80% using SVM to predict depression. In contrast, RF demonstrated better accuracy in certain tasks [13]. Research by Hong et al. [14] and Wahle et al. [10] showed that RF outperformed SVM in predicting emotional states. Similarly, boosting techniques like XGBoost, AdaBoost, and CatBoost [11], [15] also performed well, especially in handling multimodal data where boosting algorithms effectively improved model accuracy.

1) Existing Machine Learning Methods: Most of the machine learning methods employed in the selected studies leverage supervised learning, particularly for predicting emotional states such as depression and anxiety. SVM are frequently highlighted for their superior performance in handling complex datasets. For example, Yue et al. [5] and Farhan et al. [9] demonstrated the effectiveness of SVM with an RBF kernel in predicting depression. Similarly, Mastoras et al. [13] utilized SVM combined with keystroke analysis for remote depression detection, leveraging typing patterns and deletion rates to achieve an AUC of 0.89, with sensitivity and specificity of 82% and 86%, respectively. These results underscore the robustness of SVM in analyzing diverse data modalities.

In addition to SVM, boosting techniques like XGBoost and AdaBoost have shown strong performance in integrating multimodal data [11], [15]. These approaches have been extensively applied to data collected from smartphones and wearable devices, aiming to enhance the accuracy of depression and anxiety predictions.

2) Hybrid Machine Learning Methods: Hybrid machine learning methods, which combine multiple algorithms, were employed to enhance predictive performance. The combination of LSTM with CNN [16], SVM [29], or MLP [17] was frequently used, as these combinations effectively capture the complex dependencies in time-series data. For example, Kanjo et al.'s LSTM–CNN hybrid model [16] for emotion classification outperformed traditional fully connected neural networks. These hybrid methods often employ mixed features and multi-task learning [17] to further improve predictive accuracy.

3) Development of New Machine Learning Methods: In some cases, researchers developed new machine learning methods or improved existing ones to meet specific needs. Liu et al. [18] proposed a high-precision depression detection framework, which improved model accuracy through feature selection and data augmentation. Xu et al. [11] developed a collaborative filtering memory-based learning algorithm, which increased the accuracy of personalized depression detection by 5%. These newly developed methods are typically tailored to specific applications, resulting in significant performance improvements.

In summary, SVM, RF, and XGBoost are the most widely used machine learning methods in emotion prediction. Each of these methods has its own strengths and limitations, which make them suitable for different scenarios. For example, SVM is effective in handling small, high-dimensional datasets, whereas RF and XGBoost perform better with multimodal or large-scale data. By combining models and developing new techniques, researchers have further improved prediction accuracy in specific scenarios. For instance, hybrid models like LSTM-CNN effectively capture both temporal and spatial dependencies, offering a promising approach for dynamic emotion prediction. To provide a detailed comparison of these methods, Table I summarizes their key characteristics, including strengths, limitations, and best use cases.

B. Features

This paper summarizes the methods of feature collection used in emotion prediction experiments, covering three settings: laboratory, real-world, and public datasets.

In the laboratory setting, common methods involve collecting emotional features through sensors (such as heart rate monitors [19] and touch data [13]) and experimental designs (such as video stimuli [20]). Typing data [19] and heart rate variability are frequently used features to reflect participants' emotional fluctuations during the experiment. Information such as touch length, speed, and pressure can be used to predict emotions, while heart rate variability and posture [21] are also studied to explore the relationship between emotions and physiological responses. For instance, smartphone touch sensors, accelerometers, and gyroscopes are employed to monitor participants' touch and movement data. Through experimental

TABLE I
COMPARISON OF COMMON MACHINE LEARNING METHODS IN EMOTION PREDICTION

Method	Strengths	Limitations	Best Use Cases
SVM	Robust on small datasets; effective for high-dimensional data.	Requires feature scaling; less effective on large datasets.	Static emotion classification with limited data.
Random Forest	Handles high-dimensional and heterogeneous data; interpretable.	Computationally expensive for large datasets.	Emotion state prediction with mixed feature types.
Deep Learning	Excels at learning complex patterns in large datasets.	Requires large labeled datasets; lacks interpretability.	Dynamic emotion detection from time-series data.
Boosting	High accuracy; handles missing data well.	Prone to overfitting; computationally intensive.	Multimodal emotion detection with noisy data.

TABLE II
FEATURE AND METHOD COMPARISON FOR DIFFERENT STUDIES.

Citation	Features	Methods
[1]	Motion Features, Audio Features, Location Features, Phone State Features, Environmental Features, Temporal Features, Contextual Features	Logistic Regression, Random Forest, XGBoost, CatBoost, Multilayer Perceptron
[10]	Physical Activity Features, Time Spent at Home, Phone Usage Features, Geographic Movement, Number of Unique WiFi Fingerprints, Social Activity Features, Calendar Events	Support Vector Machines, Random Forest Classifier
[11]	Bluetooth Features, Calls Features, Location Features, Campus Map Features, Phone Usage Features, Sleep Features, Steps Features	Logistic Regression, Gradient Boosting Classifier
[28]	Location Information, Location Type, Weather Information, Light Level, Physiological Data, Social Activity	LSTM

designs such as typing tasks and video watching, researchers obtain real-time emotional responses from participants and use these features to predict their emotional states.

In the real-world setting, data collection methods are more diverse, with smartphones and wearable devices serving as primary tools. Smartphone sensors [9], [14] (such as GPS, accelerometers, Wi-Fi, Bluetooth, etc.) are widely used, capturing data such as location, call logs, app usage [22] , and sleep patterns. Additionally, many studies combine smartphone and wearable device data [11], such as heart rate, step count, and activity levels, to provide a more comprehensive emotional feature set. For example, some studies collect data on heart rate and skin conductance via smart wristbands, combined with smartphone screen usage, to analyze users' behavior and emotional changes. The connectivity features of smartphones are also used to examine users' social interactions and app usage patterns, reflecting their psychological states.

The third part involves directly using public datasets. With the accumulation of data, more public datasets have become available for research in emotion computing. These datasets include various features collected through smartphones, wearables, and self-reports, covering emotional, behavioral, and physiological data. For example, the StudentLife dataset [23] and Emotion Sense dataset [24] are commonly used in emotion research, containing information on location, voice, and activities, helping researchers validate their emotion recognition models. Additionally, there are lab-based emotion datasets, such as AMIGOS [25] and ASCERTAIN [26], which collect physiological signals via wearable devices and combine them with stimuli (e.g., videos) in controlled environments to analyze emotional responses.

In conclusion, different settings for emotional feature collection have their unique characteristics. Laboratory settings focus on controlled experimental data, real-world settings rely on data logged by smart devices, and public datasets offer a rich foundation for research. By utilizing these diverse data collection methods, researchers can more accurately predict and analyze emotional states, advancing the fields of affective computing and mental health.

C. Change

In current research on emotional state prediction, most studies focus primarily on the prediction of emotional states themselves, while research on changes in emotional states is relatively limited. Among the 54 selected papers, only four specifically explore changes in emotional states Table III, namely [1], [10], [27], [28]. Through an analysis of these four studies focusing on changes in emotional states, we can see that changes in emotional states play a critical role in early intervention and personalized treatment. These studies successfully achieved effective predictions of emotional changes through different machine learning methods and data features, providing valuable insights for future research on emotional states. Table III summarizes the features and methods used in these four studies.

Sultana et al. [1] explored the relationship between everyday environments and emotional states as well as transitions between them. The study used features such as motion features, audio features, location features, phone state features, environmental features, temporal features, and contextual features, and employed models such as Logistic Regression, Random Forest, XGBoost, CatBoost, and Multilayer Perceptron. Through multi-class and binary classification tasks, the study predicted both emotional states and transitions every five minutes, revealing the dynamic nature of emotional changes.

TABLE III: SUMMARY OF RESEARCH PAPERS

Citation	Algorithms	Use Cases	Key Features	Performance Metrics
[1]	Multimodal Data + Daily Sensor Data	Emotion detection using smartwatch and smartphone data	Detecting daily emotions using contextual data and emotional transitions	AUROC: 96.33%
[2]	Mobile Phone Usage Patterns	Predicting negative emotions based on mobile phone usage	Analysis of mobile phone usage patterns to detect negative emotions	Feasibility study without explicit metrics
[3]	Sensor-Assisted Weighted Average Ensemble Model	Detecting major depressive disorder using sensor data	Ensemble model combining sensor data for more accurate detection	Accuracy: 92.4%
[4]	Recurrent Neural Networks (RNN)	Forecasting depressed mood based on self-reported histories	Predicting mood changes using historical data and RNN	Root Mean Squared Error (RMSE): 0.35
[5]	Internet Usage + Machine Learning	Predicting depressive emotions based on smartphone internet usage	Predicting depressive emotions by analyzing session features of internet usage	F1 score: 0.80
[7]	Ecological Momentary Assessment (EMA)	Assessing day-to-day mood using mobile phone data	Unobtrusive mood assessment using mobile phone-based EMA	Feasibility study, no explicit metrics provided
[8]	Multiclass Emotion Prediction	Predicting emotions using heart rate and virtual reality stimuli	Multiclass emotion prediction based on heart rate and VR stimuli	Accuracy: 85%
[9]	Multi-view Bi-Clustering	Identifying smartphone sensing features indicative of depression	Clustering features from multiple views (sensor data) to refine depression prediction	Not mentioned (feasibility study)
[10]	Mobile Sensing and Support	Providing real-time support for people with depression using mobile sensing	Mobile sensing data used to support and monitor patients with depression in real-world settings	Feasibility study, no explicit metrics provided
[11]	Collaborative Filtering + Personalized Behavior Modeling	Personalized depression detection using collaborative filtering	Enhanced model performance through weighted feature selection in personalized behavior modeling	Accuracy increased by 5.1%, F1 score improved by 5.5%
[12]	WiFi Metadata + Random Forest	Large-scale automatic depression screening using WiFi metadata	Screening for depression using WiFi location metadata	F1 score: 0.85
[13]	SVM + Keystroke Analysis	Remote depression detection using typing patterns	Evaluation of mental health through typing rhythms and deletion rates	AUC: 0.89, Sensitivity: 82%, Specificity: 86%
[14]	Feature-Based Machine Learning	Predicting depression using smartphone data	Use of depressive symptom features extracted from smartphone usage data	Accuracy: 85.7%
[15]	Ensemble Learning	Improved emotion prediction using ensemble learning	Enhanced accuracy through multiple base learners	F1 score improved by 15%
[16]	CNN + RNN	Emotion detection using CNN and RNN models	Improved emotion recognition accuracy by combining CNN and RNN	AUC: 0.88
[17]	Multitask Learning + Calendar Event Data	Mood prediction based on calendar events	Improved accuracy through multitask learning for handling calendar events and mood fluctuations	Prediction accuracy higher than traditional methods
[18]	HADD + Multimodal Data	High-accuracy detection of depressive symptoms	Improved accuracy through enhanced data selection and two-stage detection	Accuracy: 98%, F1 score: 0.95
[19]	TapSense	Emotion detection using typing patterns	Emotion detection using typing patterns combined with deep learning	Accuracy: 88%
[20]	Heart Rate Data + Wearable Devices	Emotion recognition using heart rate data	Monitoring three emotions—happiness, sadness, and calm—using heart rate	Recognition accuracy: 78%
[21]	Capacitive Sensing	Detecting emotions using capacitively sensed data from a couch	Learning emotions based on capacitive sensing technology embedded in furniture	Accuracy: 90%
[22]	SVM + Daily Log Data	Happiness prediction using supervised learning	Predicting happiness using data from smartwatches and smartphones	Accuracy: 82.6%
[27]	Machine Learning + Feature Selection	Detecting depression and predicting its onset using passive sensing data	Longitudinal symptom data with robust feature selection	AUROC: 0.87
[28]	Personalized Deep Learning	Predicting anxiety symptom changes using smartphone sensors	Personalized models based on ecological momentary assessments (EMA)	Accuracy: 89%
[29]	SVM + LSTM	Emotion state detection combining LSTM and SVM	Emotion detection using time-series data and SVM	Emotion detection accuracy: 85%

Wahle et al. [10] focused on the effectiveness of interventions, with changes in depression symptoms being a key outcome. The study used physical activity features, time spent at home, phone usage features, geographic movement, unique WiFi fingerprints, social activity features, and calendar events, and employed Support Vector Machines (SVM) and Random Forest Classifiers to predict changes in depression severity. PHQ-9 tests were conducted every two weeks, and the results showed that the proposed interventions gradually reduced participants' depressive symptoms as their PHQ-9 scores decreased.

Chikersal et al. [27] analyzed emotional state changes among 138 university students, using the Beck Depression Inventory-II (BDI-II) to assess depressive symptoms and comparing the changes between the beginning and the end of the semester. The study found that the number of students experiencing depression increased from 20 at the beginning of the semester to 56 at the end. The study used Bluetooth features, call features, location features, campus map features, phone usage features, sleep features, and step features. By employing Logistic Regression and Gradient Boosting Classifier, the researchers were able to predict the worsening of depressive symptoms by the fifth week of the semester, significantly outperforming baseline accuracy, thus providing a useful tool for early intervention.

Jacobson and Bhattacharya [28] collected sensor data over a two-week period to predict changes in anxiety symptoms. Based on features such as location information, location type, weather information, light levels, physiological data, and social activity, the study utilized Long Short-Term Memory (LSTM) models. The models successfully predicted overall changes in anxiety symptoms, and through personalized models, they also predicted symptom changes on an hourly basis. The results showed that anxiety and avoidance symptoms can change significantly within short periods, providing an important basis for timely interventions.

In summary, location information was widely used as a key feature in these four studies, demonstrating its crucial role in predicting emotional states and their changes. Location data not only reflects users' daily activities and social environments but can also be combined with other sensor data (e.g., step counts, physical activity) to improve prediction accuracy. Additionally, the broad use of ensemble learning methods (such as Random Forest, XGBoost, and CatBoost) further enhanced the models' ability to generalize when dealing with complex emotional state data. These approaches show that by incorporating multi-level features and ensemble learning methods, researchers can effectively improve the precision and timeliness of predictions for emotional state changes.

IV. Conclusion

A. Conclusion and Future Research Directions

This paper reviewed the application of smartphones and smartwatches in combination with machine learning methods for depression, anxiety, and emotional prediction. The primary methods can be categorized into three types: classical methods like SVM and RF, the combination of multiple methods to improve results, and innovative applications of novel methods. Among these, SVM and RF are the most commonly used benchmark methods, widely applied in emotion prediction. Each of these methods has distinct strengths and limitations, making them suitable for different scenarios. For example, SVM excels in small-scale, high-dimensional datasets but struggles with multimodal data, while RF and XGBoost are more robust for large and diverse datasets, yet often lack interpretability. Deep learning models, such as LSTM-CNN hybrids, show potential for dynamic emotional changes but require substantial labeled data and computational resources.

Future research could continue exploring new methods, particularly for the dynamic detection of emotional changes, an area that has only been addressed by a few studies. Passive data collection in daily life via smart devices has been widely applied and can be extended to other devices such as wristbands and new-generation wearable technologies. Enhancing generalizability across diverse datasets and improving interpretability are critical challenges that must be addressed for broader clinical adoption.

In addition, the sensitive nature of psychological health data collected from wearable devices highlights the need for robust privacy-preserving mechanisms. Advanced methods such as federated learning and secure multi-party computation offer promising directions to enhance data security while enabling meaningful insights from distributed datasets. Addressing these privacy and ethical challenges will not only build trust in wearable technology applications but also ensure their ethical deployment in mental health research and interventions.

B. Limitations

This study reviewed literature published between 2013 and 2023; however, due to the inclusion criteria, certain studies were excluded, such as those utilizing alternative data tools or focusing on specific populations. Furthermore, while this paper primarily emphasizes the technical and methodological aspects of machine learning and wearable technology, discussions surrounding data privacy, ethical considerations, and real-world implementation challenges remain limited. These topics are particularly pertinent given the sensitive nature of the data collected and merit comprehensive investigation in future research. Despite these limitations, this paper offers a valuable academic overview of the field and highlights promising avenues for advancing emotion prediction through wearable devices and machine learning.

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