AI ML ENABLED WEARABLE SMART SENSORS DETECTING PSYCHOLOGICAL DISORDERS

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***Abstract*—With the rapid change in the advancement of technologies, every field has turned depending upon engineering. However, due to the use of conventional techniques, progress in the field of psychology has been gradual. This paper focuses on the goal of various smart or intelligent sensors for healthcare and medical applications, which use sensing technologies and various measurement techniques for healthcare, particularly psychological disorders. These sensors cope with the improvised services of acute and chronic disorders. The latest technology uses ML and AI to provide better treatment and accuracy. The paper shows how wearable technology and AI are interlinked to provide patient behavior patterns. We have analyzed AI algorithms used in these sensors and how some specific psychological disorders benefit from using the same technology.**

Keywords: AI, ML, Sensor, ASD, ADHD, ID.

I. INTRODUCTION

The evolution of healthcare technology using mechatronics, the Internet of Things, wearable technology, and Smart Sensors are all being used in the development of healthcare technology to extend average life expectancy and offer numerous creative answers to major problems in the field. Several screening tests are used in the diagnostic and therapeutic processes to design, validate, and apply these sensors' functionality.

So that they can do tasks indefinitely, machines should be trained using algorithms and datasets. Due to doctors' busy schedules, AI gadgets can swiftly build rapport with patients, but they can only speak to one user at a time. Patients do not have to worry about revealing their private information to others when it comes to privacy because AI robots can readily access it, which makes them feel better. Machines are made to work continuously in the patient's favor rather than making them depressed or afflicted with any other psychiatric condition.

II. RELATED WORK

The primary method of operation for smart sensors is the consumption of data from changing physical variables such as temperature, pressure, and mass. Such sensors contain a unique processor called a (DMP) Digital Motion Processor, which enables the sensors to analyze the data they are ingesting from their external environment. Simply by identifying physical signals and converting them into electrical signals, measurements are obtained. Monitoring and measuring things like temperature, traffic, and industrial applications would benefit from this. The operation is more complicated than that of those a Base sensor. It is a single sensor with signal processing. A smart sensor, on the other hand, is made up of a base sensor, a power source, memory space for the CPU, and a communication module. Smart sensors are capable of self-calibration and self-assessment; sometimes, this property of self-correcting can detect the faults of the smart sensor. The smart sensor can detect location without the configuration function, which prevents installation problems. The verification function can be used in a variety of ways, including continuous monitoring of sensor behavior using a set of supervisory circuits or equipment that is run inside the sensor. Finally, the sensor may communicate with the primary CPU. [1]

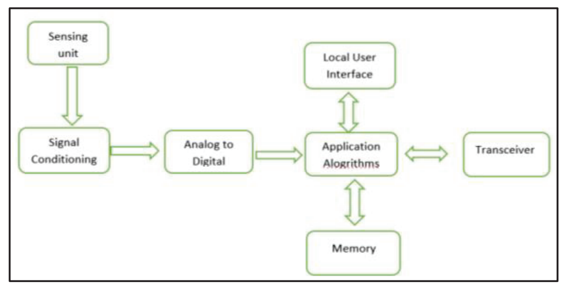

Fig1 - Maintaining the Integrity of the Specifications

A. Sensors used in healthcare

A person's life was profoundly altered by IoT. As with smart health or e-health, patients can wear sensors at home, at work, or in hospitals. These sensors keep an eye on a person's health and alert the appropriate people if anything seems off. Hospitals can better manage patient care with the aid of smart bands worn by both patients and medical staff. Sensors can be used to administer vaccines, monitor organic compounds, regulate medical equipment, and keep an eye on the vital signs of elderly patients.

It's possible to provide warnings about a person's bad habits, health conditions, or even UV sun exposure. Smart bands, often referred to as wearable sensors, hospital staff and patients' clothing, contribute to the management of the patient's care. Injecting vaccinations, monitoring chemical substances, and operating medical equipment can all be done with sensors, as well as elderly patients' vital signs. It's possible to provide warnings about poor habits, medical issues, or UV sun exposure to an individual. [2]

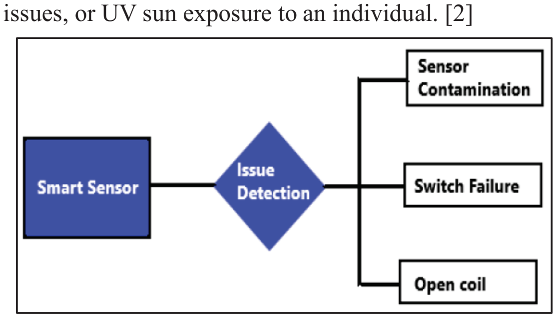

Fig2 – Issue detection of a smart sensor

2023 13th International Conference on Cloud Computing, Data Science & Engineering (Confluence) | 978-1-6654-6263-1/23/$31.00 ©2023 IEEE | DOI: 10.1109/Confluence56041.2023.10048832

B. Types of Sensors

- *Biopotential electrodes*

  Bioelectric signals in living tissues are captured by electrophysiological sensors, another term for them. The ability of electrophysiological sensors to continuously monitor electrophysiological processes will be very helpful for applications in diagnostics, rehabilitation, sports performance tracking, and human-machine interfaces.

- *Electrochemical electrodes*

  In the fields of fitness, healthcare, sports, security surveillance, forensics, and wearable electrochemical sensors are becoming more popular. For continuous measurement of electrolytes, metabolites, pH, and significant biochemicals in bodily fluids (such as glucose and lactate), skin-mounted devices have been developed. These devices can warn users of dehydration, weariness, and early illness symptoms. Applications for a wide range of wearable and electrochemical technologies are made possible by combining their best features.

- *Wearable environmental sensors*

  Keep an eye on things like gas concentration, light intensity, and humidity. Such knowledge can assist in defending humans from hazardous surroundings by revealing how the environment influences healthcare and allowing interactions between people, robotics, and the environment.[3]

- *Micromechanics, microelectronics,*

  Acute sensors that are quicker and produce adequate data returns while consuming less power have been developed via other technologies. Here, one of the critical indicators of a user's health is their body temperature. This is regarded as the primary parameter since any changes in the body's internal environment immediately impact and modify body temperature. The cause of body temperature fluctuation could be an infection or a heart attack. The body's temperature changes when a patient experiences any unexpected mental shocks. This can be monitored with a thermometer, a long-used instrument, but today temperature sensors with electrical and electronic components can take its place.

  An accelerometer sensor is used to track the patient's movement, and the frequency range is increased to lower some form of hypertension if any type of mental illness in the human body needs to be accelerated. Based on capacity, there are many sorts of accelerometers for various types of mental diseases. Finding heart rate changes brought on by stress, exercise, or other factors is another wearable technology that is increasingly commonly employed. Heart attacks can be prevented and monitored using these devices.

C. Introduction to AI

The benefits of AI technology are more significant for patients who oversee their medical care. In situations like this, mobile devices are used to perform a question-and-answer survey to find out the health state of the patients. Since no medical care is offered there, any patient found there can be treated quickly and easily. AI devices are more useful in the area of healthcare for people. In comparison to humans, current robots and other intelligent equipment help with more complicated tasks, which results in higher efficiency and more precise values. Additionally, sensors can be incorporated into various additional devices, and these particular gadgets can be worn on the skin.

D. Limitations of AI

Doctors' assessments of psychiatric problems are based on their emotional values since computational technology treatment is dependent on AI technology.

• Patients who entirely rely on AI technology run the risk of falling behind and worrying clinicians if they rely on the outcomes of AI devices.

•AI can be developed and tested on real humans; if it initially functions flawlessly, that is great, but if it later develops a bug or ceases functioning, users may experience problems. A gadget made for all patients may not be beneficial for all patients because each person's disease pattern is unique, which is a major drawback of developing AI technology too quickly.

• Mistaken negative or positive results are not considered by artificial intelligence, and training data might lead to X-ray analysis flaws that AI cannot fix.

• Using the values that AI tools supply, doctors may easily approve all the criteria because they have no reason to doubt the accuracy of these data.

• While AI systems may complete multiple jobs at once, it might be not easy to keep track of everything they accomplish

E. Wearable Technology and Artificial Intelligence in Psychological Disorder

Wearable equipment can be used to communicate with other systems. Integration is done on other systems to assess value. Wearable smart gadgets may be used by patients with mental health issues, such as those who have trouble handling sudden shocks in the world of investments, to predict which investments would perform better and to decrease any mental shock that may arise from a negative outcome. The term "wearable technology" describes gadgets that keep track of a person's daily routine and personal habits. Electronic instruments like ECG, ballistocardiograph (BCG), and other valuable tools can all be used to capture measurements for heart rate, body temperature, mental state, and other parameters. Our hand watches, ankles, clothing, and lenses, among other devices we use every day, all have wearable electronics attached to them. Additionally, sensors can be incorporated into various additional devices, and these particular gadgets can be worn on the skin.

Some devices are used to keep track of all recorded values so that we can use mobile phones to preserve them. The issue at hand was difficulties with wearable technology in the healthcare industry. It was people's worries about their privacy when using wearable technology. The primary topic of discussion turned into a worst-case scenario regarding privacy. [4]

F. How AI and wearable technology are interlinked

The advancement of AI in medicine has been gradual, particularly in the fields of psychiatry and adolescent psychiatry. In order to categorise some problems, including heart issues, epilepsy, and different types of cancer, the majority of prior research in psychiatry has either focused on NLP [5]. Additionally, due to the sustained regulated collaboration between engineers, mental health professionals, and data scientists, the adoption of these approaches in psychiatric practice has lagged behind that of psychiatry and other medical fields. Wearables are frequently used in the healthcare sector to collect, analyse, and stay in touch with patient health data [6]. By keeping health records, people and the required medical personnel can be informed about changing health indicators—a few illustrations of those mentioned above. A study by Ilias Tachmazidis [7] analysed records of an adult who had diagnoses over the previous few years and created a hybrid approach made up of two dissimilar models: a machine-learning model trained on information from previous cases and a knowledge model that used knowledge engineering to capture the expertise of medical experts. The final method with a 95% accuracy rate for the data that is currently available.

G How algorithms of AI applications used in detecting the psychiatric Disorders

Machine learning is a subset of AI applications that learns and alters parameters independently to do a specific task with steadily increasing accuracy. Machine learning approaches can be divided into two categories: supervised learning and unsupervised learning. Gray matter structure qualities with cortical volume, thickness, and area surface, as well as white matter diffusion properties, are MR features that have been assessed using machine learning methods.

Logistic regression: Logit models, often called logistic models, are frequently employed statistical models in statistics, and the LR algorithm is a critical AI approach. In recent studies, LR models have been widely employed to pinpoint psychiatric issues. For instance, Hagen et al. scrutinize the relationships between two cognitive screening tests and psychological balance [8] using an LR approach. The findings showed that performance-based evaluation could lessen the negative impacts of mental stress on cognitive screening. Additionally, Barker et al. used multivariable LR models to predict one-month psychiatric readmission. [9]. Their data have improved readmission prediction and are regarded as key predictors for psychiatric readmission. Shen et al. created a classification and regression tree-based risk stratification model to calculate the odds ratio (OR) of mental comorbidities.

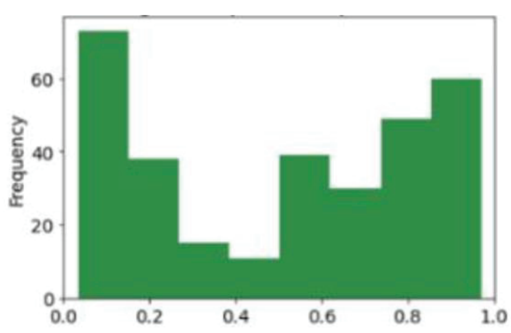

Fig 3- Histogram of predicted probability of treatment

Bayesian model: The term "naive Bayes classifier" in AI refers to a classification algorithm in general. A classification technique called the naive Bayesian approach is based on the Bayes theorem and the characteristic condition-independent hypothesis.

Bayesian models have frequently been used in recent studies to diagnose the psychiatric disorder. For instance, the Strüngmann Forum on Computational Psychiatry suggested utilizing Bayesian inference to link symptoms, latent theoretical notions, and underlying causes (genetic and societal processes). Additionally, Grove et al. investigated the connection between visual integration and general cognition using a Bayesian model comparison approach. The findings demonstrated that a Bayesian model might compare disease classification schemes and have shared psychopathological data from diagnostic categories. The Bayes Theorem is stated as follows: Let E1, E2, E3,..., EnE1, E2, E3,..., En be a collection of events connected to a sample space S, where all E1, E2, E3,..., EnE1, E2, E3,..., En events have a probability of occurrence greater than zero and together they constitute a partition of S. If A is any event and E1or E2 or E3...or En E1or E2or E3...or En occurs, then the Bayes Theorem states that

P(Ei|A)=P(Ei)P(A|Ei)∑nk=1P(Ek)P(A|Ek),i=1,2,3,...,n

Here, Eii Ejj =, where I j. (i.e.) They are mutually exhaustive events.

P(Ei|A)=P(Ei)P(A|Ei)k=1nP(Ek)P(A|Ek),i=1,2,3,...,n

The sample space should be equal to the union of all the partition's occurrences.

A decision tree is a flow diagram that resembles a flowchart and displays the many results of a set of decisions, including utility and chance event outcomes. One of the popular and commonly applied algorithms for supervised categorization learning is the usage of decision trees. A tree in AI is a predictive model that shows the relationship between object values and object characteristics. A purity-based heuristic is used by the majority of contemporary decision tree learning algorithms [10]. They used a decision tree to identify children who were at risk of developing an anxiety disorder, and their research found that it can reliably predict GAD and SAD cases up to 96% of the time. Sattler et al. Using information from the Spence Children's Anxiety Scale (SCAS) and SCAS-P obsessive-compulsive disorder subscales, two screening algorithms were developed to detect OCD in a combined clinical and community sample of kids and families.[11].

The findings demonstrated that the algorithms could diagnose obsessive-compulsive disorder with as little as 67%–83% fewer SCAS-P items while maintaining the character of the entire subscales

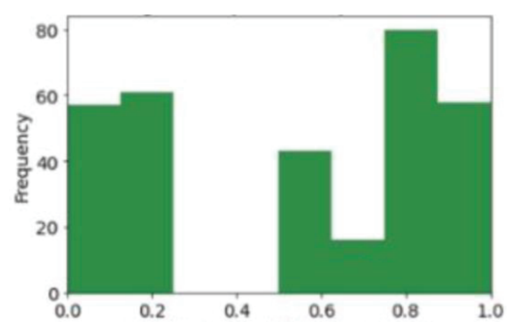

Fig4 - Histogram of predicted probability of treatment

E. Psychological disorder symptoms

Consequently, progress in psychiatry is modest despite AI's innovations and the reshaping of medicine.

ASD(Autism spectrum disorder): Therapists would be able to monitor a child's engagement using an AI device in order to tailor therapy to the unique needs of each child. Another study used an accelerometer wrist strap along with an app for smartphones called MyMedia and MySchedule to assess EEG and ECG. Six main emotions—joy, unhappiness, fear, disgust, surprise, and rage—were what the app was designed to record. The sensors and facial recognition system measured variables like pupil dilation, heart rate, skin conductance, HR variability, concentration, blood pressure, and attention levels through a watch, headset, and chest strap. This approach might give autistic children and their carers a personalized way to comprehend and control their emotions. Wearable ankle sensors were utilized by Wilson et al. [12-15] to identify ASD in young patients. Since many believe that motor impairment may be predictive of ASD, the research used wearable ankle sensors to track full-day motor activity in newborns with a high familial risk for the disorder. A 3D gyroscope, 3D magnetometer, and 3D accelerometer were all used.

ADHD(Attention-deficit/hyperactivity disorder): This study of ADHD focused solely on the hyperactivity aspect of ADHD and employed an application to gather movement data using an accelerometer. In separate research, scholars used data from the accelerometer and gyroscope of a smartwatch to analyze the behavior of kids with ADHD [20–23]. A study [24–28] investigated whether activity, circadian rhythm, and sleep data could be used to distinguish between children with bipolar disorder and children with ADHD. They employed an Actigraphy belt (acute myocardial infarction motion logger). The results showed that youngsters with ADHD and those who had bipolar disorder had various sleep schedules and estimates of their circadian strength.

According to this study, wearable technology and artificial intelligence may help in the diagnosis of many overlapping paediatric diseases.

ID (Intellectual disability): Redd et al. [29] investigated the possibility of using physiological signals like skin temperature, skin electrodermal activity, and heart rate to predict meltdowns and enabled earlier and much more efficient intervention. These predictions were made with the aid of a wrist-worn biosensor that also measured the blood volume passivity, the 5electrodermal activity of the skin, the overall motion and activity, a 3-axis accelerometer, and the temperature of the periphery of the skin.

F. Limitations of Algorithms

Tree: A minor change in the raw data might result in a significant variation in the decision tree's structure, which can convey results that differ from what users would typically receive in a given situation. For instance, because accuracy varies with flaws, a change in heart rate frequency when capturing the data of an ASD patient may result in a false negative. Decision trees don't perform well when predicting the outcome of a continuous variable.

Logistic regression shouldn't be utilised if there are fewer data points than features since overfitting could happen. The assumption that the connection between the dependent variables and the independent variables is linear is the main problem with L.R. Only discrete functions may be predicted using it successfully. As a result, the logarithmic regression's dependent variable is the only part of the discrete number set that may be used. [30-32].

III. CONCLUSION AND RESULT

The information about the application of wearable AI in patients with ID, ASD, and ADHD has been thoroughly examined in this scoping review. We discovered significant methodological and performance variability in our scoping assessment of AI studies in psychiatry. Nevertheless, our scoping examination identified several significant advantages for each of the diseases covered by this study. First, a variety of wearable technology sensors, including heart rate, accelerometers, and sleep, have shown promise in the diagnosis and prognostication of adult psychiatric diseases. This paper concluded with some results regarding Psychological disorders like changes in sleep patterns high heart rate fluctuations, abnormal hyperactivity, motion restrictions, and skin conduction levels increase were observed. In addition, professional annotations of young children's behavior data-driven analytical solutions from wearables forecast when a child may develop mental illnesses. This sort of integration is essential for enabling remote monitoring, and Psychiatric services will probably help reduce inequities in the field of mental health. Large-scale research has not yet been conducted on the topic of psychiatric diseases (including genetics, environment, and exposures) in relation to diagnosis, treatment, and management. In order to fully reap the rewards of AI techniques, the incorporation of wearables in patient psychiatry research needs goes beyond strictly regulated study environments.

IV. ANNEXURE

Study	Year	Diagnosis	Age	Device	Remarks
Bilecci et al	2018	ASD	18-36 months	ECG[a] with chest strap (Shim- mer)	High HR[b] with an average level of 125

Bilecci et al	2016	Autistic Spectrum	4-25years	EEG with headset and CECG chest strap (EEG-Enobio wireless device)	Excess Beta waves at the frontal sides of the brain show the activity of poor sensory integration and excitability and anxiety.
Di Palma et al 2017	2017	Autistic Spectrum	5-9 year	ECG chest strap (based off Shimmer)	HF Heart period Fluctuation in respiratory frequency
Faedda et al	2016	BP or ADHD	5-18 year	ActiGraph belt (AMIo mo-tionlogger)	Collection of data on sleep, circadian rhythmicity, and hyperactivity was anormal.
Fioriello et al	2020	ASD or LD[d]	10-28 years	ECG chest strap	Patterns were formed of high heart rates
Gayet al	2014	Autistic spectrum	4-5 years	Accelerometer with wrist strap (Affectiva Q Sensor), EEG headset (MindWave Mo- bile), ECG chest strap (Zephyr BioHarness), and mobile phone app (My-Media)	Monitoring autistic behaviour activities which may be harmful to the person
Goodwin et al	2019	Autistic Spectrum	6-18 years	c Wrist-worn biosensor (Empatica E4)	Predicts the rise in HR
	2016	Autistic Spectrum	3-15 years	Wrist-worn biosensor	EDA[e] may provide an early indication of subsequent problem behaviour.
Kushki et al	2015	Autistic Spectrum	Not Specified	ECG chest strap (Shimmer)	Patterns were formed of high heart rates
Leikauf et al	2021	Attention Disorder	8-13 years	Smart watch app (Stop-Watch)	Datasets of different frequencies of HR are gathered.
Lin et al	2020	Attention Disorder	5-10 years	Smart watch (Asus Zen-Watch 3)	The gyroscope detects the motion of the patient and in-hand records all the hyper-activities.
McGinnis et al	2021	Intellectual Disorder	4-8years	IMU with chest strap and headband	Chest trap helps in detecting respiration rate, posture analysis, seismo cardiography of an ID patient.
McGinnis et al	2019	Intellectual Disorder	3-5 years	IMU with chest strap	Chest trap helps in detecting respiration rate, posture analysis, and seismo cardiography of an ID patient.
Min et al	2011	Autistic Disorder	3-6 years	Accelerometers worn on wrists, ankles, and upper body	Accelerometers are used to detect pulse rate, motion, flapping etc.
Munoz-Organero et al	2019	Attention Disorder	6-17 years	Accelerometers which are wrist-worn and ankle-worn (Run- scribe inertial sensors)	Accelerometers also detect motion patterns and acceleration. Modification of activity is done, and over-active behaviour is also detected.
Ouyang et al	2020	Attention disorder	5-13 years	Accelerometer embedded in a smart watch	Unidirectional motions pattern is detected in ADHD patients.
Pfeiffer et al	2019	Attention Disorder	8-17years	wrist-worn with biosensor (Empatica E4)	Autonomic arousal of skin's conduction levels.
Redd et al	2020	Intellectual Disorder	8-14 years	worn on the wrist with biosensor (Empatica E4)	The skin's temperature, mobility, and electrical properties all exhibit variations.

Wilson et al	2021	Autistic Disorder	1-3 years	Ankle-worn with biosensors of (APDM Opal; APDM Wearable Technologies)	Autonomic arousal of skin conduction levels.

Abbreviations

[a]ECG: Electrocardiogram

[b]HR : Heart Rate

[c]BP: Blood Pressure

[d]LD: Learning Disability

[e]EDA: Electrodermal activity

[f]HRV: Heart Rate Variability

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