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Preface

For the third time we were able to hold our PhD workshop "Research is Calling" on smart medical devices and systems, this time in Berlin again. This unique workshop brings together young scientists from computer science and medicine to provide a forum to discuss the very latest approaches to smart medical devices and systems. This year, for the first time, it is possible to publish corresponding workshop proceedings via the publication service of the Brandenburg Technical University (BTU).

In our view, this format can create true interdisciplinarity because everyone presents their ideas and interim results to colleagues from a wide variety of disciplines and, conversely, hears and sees the latest from many other specialties. This forum is the vehicle for initiating new collaborations and planning joint research projects.

The 'Cottbus project' emerged from personal partnerships between 'technicians' and 'physicians' and was planned from the beginning as a platform and an offer: as a *platform* for free and fully open scientific exchange and discourse, as an *offer* to all who are interested, also and gladly beyond Brandenburg.

Begun as a "PhD Colloquium", Cottbus' "Research is Calling" is an ideas laboratory for young scientists. Cottbus is to establish a university medical faculty in the next few years as part of the structural change program following the coal phase-out.

From our point of view, this lab is an important building block to establish cross-sectional issues right at the interface between medicine and technology, a culture of open discourse and scientific dialogue.

The workshop covers the following topics in particular: Smart sensors for medical applications, Low-power wearable sensors, artificial intelligence for medical applications, medical robots, algorithms for medical applications, applications and case studies.

Despite the pandemic situation the workshop could be held in presence. In five exciting presentations new ideas and cooperation possibilities were shown. Two keynotes (including Alina Nechyporenko, Marcus Frohme as special guests) and a dinner rounded off the program.

At this point we would like to thank all participants, the reviewers, and the organizers, Stefan Scharoba and Kathleen Galke.

We look forward to establishing this event as permanent and reaching an ever-growing audience.

March, 2022
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An Application Scenario for Humanoid Robots in Assisted Living Environment: CheckupAI

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Abstract—Recent Pandemics in the last two decades have shown us the importance of contact avoidance, social distancing and quarantine. Healthcare sector takes a big toll in such circumstances as contact-less care and support to patients becomes extremely risky but unavoidable. Robots in Assisted Living Environment (ALE) combined with AI and Machine Learning Techniques are one of the great ways to overcome this problem. In this paper, we propose an application scenario so-called CheckupAI where a humanoid (Pepper Robot) can be used to interact with the patients in isolated rooms, thereby, communicating the status and storing checkup reports on a database server to the staff by avoiding physical contact as much as possible.

Index Terms—component, formatting, style, styling, insert

I. INTRODUCTION

Social distancing and increasing home office practices are bringing remote robotic assistance in healthcare facilities into prominence [1, 2, 3]. New robots have been developed to perform pandemic tasks. Existing robots have also been employed in new ways to help allay the fears of healthcare personnel in highly contagious environments. One such humanoid robot is the pepper robot [4] which supported by its emotional engine can interact verbally with patients and transmit query data to servers for nurses and doctors.

II. BACKGROUND

A. Previous Projects

We have demonstrated similar ideas and projects in the past where robots have been of great usability in assisted living environments [5]. In this work, we introduced CleanMeAI and InjectMeAI as use cases for humanoid robots being helpful in situations like vaccination and sanitization while minimizing human contact. In CleanMeAI, the robot detects door handles e.g. in a hospital building, checks the status and sanitizes them in case it was not sanitized. While InjectMeAI as the name implies, is step-forward in assisted vaccination where it can detect a human and estimate its pose for vaccination.

B. Problem Statement

Constant monitoring of patients and regular reminders for medicinal injection, even in highly contagious circumstances are sometimes necessary [3]. This has been partly achieved with the introduction of closed-circuit cameras in wards and assisted living environments [6]. However, the information

obtained on patients is usually limited. A humanoid robot in addition to monitoring and generating reminders for patients, can consult with patients, ask questions, obtain answers and transmit real time query information for quick response.

III. OBJECTIVE AND PROPOSED METHODOLOGY

A. Objective

The main objective is to train a pepper robot to perform an oversight role by recognizing patients and relaying reminders. It will ask pertinent questions and store query results on forms designated by health workers. Doctors can depend on this information to deliver better service.

B. Methodology

The humanoid robot will be able to detect [7] if a patient has fallen from the bed, also make requests and reply to patients verbally as shown in Figure 1.

Salient response from patients will then be converted in text and stored in an MS-Access database. Moreover, alerts can be sent via SMS or Email to medical staff who can access the forms remotely.

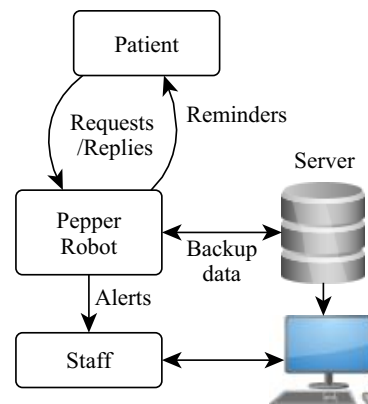


Fig. 1. Pepper Robot based Consultation Setup

C. Implementation

The humanoid robot is endowed with four microphones, two RGB cameras and stereo speakers that support its emotion

engine to interact with the environment. After scanning its surroundings to detect human presence, it will activate a speech module containing checkup questions and proceed to give reminders where available. It will also determine if patient is fallen on the ground. Such an application is possible using pose detection and predicting the fall by means of trained neural networks. A continuous feed of video images through the robot's camera and dedicated close-circuit cameras inside a patient's room can help to obtain real-time status to be fed to trained neural networks. After interacting with the patient, relevant information will be backed up on a server and staff alerted. A flowchart explaining the proposed implementation is shown in Figure 2.

D. Evaluation

A time motion study has been conducted to document and to compare nursing activities within 12 hour shifts in relation to communication, hands on tasks and locations within healthcare facilities[8]. Besides transcribing and reviewing electronic healthcare records, nurses may walk up to 40km per shift just to check on patients. The intervention of our robotic system both reduces the need for transcription and curtails the walking distance per shift per nurse. Patient status update is instantly available to nurses and doctors alike.

IV. CONCLUSION

The introduction of humanoid robots to handling simple check up activities in healthcare facilities, is a good solution for augmenting the efforts of nurses at interacting with patients, transcribing information and making it instantly available to all interested parties, however remote they may be.

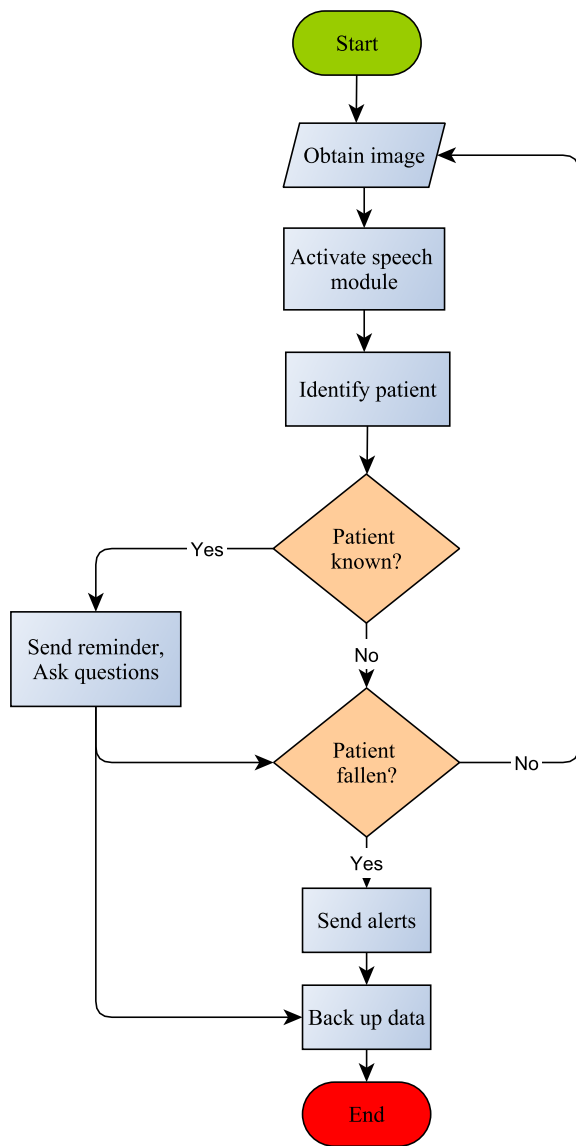


Fig. 2. Algorithmic Flowchart

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Heart rate variability (HRV) and its predictive value for the cardiac patient at risk

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Abstract—It is well known that heart rate variability (HRV) can be used as a prognostic marker for cardiac health: Low HRV predicts a worse prognosis for cardiac patients at risk. Basing HRV measurements on a more easily accessible method such as photoplethysmography (PPG) instead of the conventional ECG has many advantages to screen larger populations and track down patients with a high-risk of serious adverse events.

Index Terms—heart rate variability, patient at risk, photoplethysmography, digital health.

I. BACKGROUND

A. Diagnostics to define HRV

There are different ways to measure HRV even though there is not a clearly defined golden standard. Most of the easy-to-use tools are considered complementary diagnostic methods [1]. Hodgart & Macfarlane (2004) showed that the use of a 10 second ECG strip for HRV may be beneficial compared to a conventional 24-h ECG [2]. They suggested to screen a larger healthy population, determine HRV and apply the results to high-risk patients. Another option for determining HRV is photoplethysmography (PPG). PPG is used by the Apple Watch to detect, record, and evaluate heart rate (as well as oxygen saturation) [3]. By using infrared LEDs and a photodetector, blood volume changes in the microvasculature are recognized. Each pulse signal is identified as an R wave which enables determining heart rate and its regularity [4]. The Apple Watch's algorithm has shown that 34% of all screened patients suffered from previously unknown atrial fibrillation [5].

B. HRV as a prognostic marker for cardiac health

It is well known that HRV can be used as a prognostic marker for overall cardiac health [6,7]. Decreased HRV implies a worse outcome [8,9,10]. Low HRV early after an acute myocardial infarction (AMI) indicates a high risk of sudden cardiac death [11]. The same holds true for patients with chronic heart failure: low HRV (or computational variables derived from it, in particular SDNN¹) is strongly predictive of higher mortality and appears to be a better marker than most other conventional clinical measures [12]. De Gaetano et al. [13] developed an algorithm to distinguish between 'normal' and 'ischaemic' heartbeats on ECG. This is done using RR

intervals and radial basis functions [13, 14]. This method has been validated on the European ST-T database and provides high reliability, but unfortunately low accuracy [13, 14].

II. METHODS: IDEAS FOR FUTURE STUDY DESIGNS

A. HRV as a prognostic cardiac marker for patients with high risk of reinfarction

A prospective clinical trial is needed to further evaluate HRV as a prognostic cardiac marker after AMI on the one hand, and to compare different diagnostic options, their validity and reproducibility on the other. Routine medical care after AMI already includes 10 second ECG strips; the proposed study design should also include HRV measurements using PPG from smartwatches and, if feasible, in-ear blood pressure sensors, so that all three methods could be compared. In addition, an algorithm that differentiates between physiologic and ischaemic heartbeats can be further tested with regards to each diagnostic tool [13]. An estimated sample size of at least 3*30 (N=90) is required for this study design. HRV measurements could be taken immediately after diagnosis, 3 weeks, 9 weeks, 12 months, and 24 months after infarction. The dates for the measurements also include a general follow-up on cardiac events within this period that have not been recorded earlier.

III. CONCLUSION

HRV could be used to regularly follow up on cardiac patients at risk by taking advantage of it being a highly reproducible and cost-effective prognostic marker. Ischaemia or even an impending heart attack could be detected early (by the patient, their relatives or their family doctor) so that medical help can be sought quickly. Once reliably evaluated, a smart watch could have the option to alarm an ambulance on its own.

¹SDNN = standard deviation of NN intervals

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Artificial Intelligence (AI) in Psychiatry: A New Assistance Tool in Psychiatric Diagnostics?

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Abstract—Artificial intelligence (AI) has not yet played any role in psychosomatics and psychiatry, even though its applications are becoming increasingly important in cardiology and intensive care medicine, for example.

This paper discusses applications of AI in psychological and psychiatric diagnostics. It discusses scenarios in which AI could play a decisive role and support the entire concept of psychiatric care. At the same time, it aims to clarify the opportunities, but also the risks, of AI in this particular field. overall treatment procedure.

Index Terms—Artificial Intelligence, Machine Learning, psychological, psychiatric, diagnosis

I. INTRODUCTION

A few years ago, a story became popular, in which TARGET, a US supermarket chain, allegedly used Big Data to predict the pregnancy of a teenage girl. What is particularly extraordinary about this story is that the girl's father did not yet know about the pregnancy. [1] Although it is not clear whether this actually happened or is just another urban legend, it could be a very real scenario where AI based on Big Data is used to predict changes in life circumstances or even the mental health of people. [2]

AI has made significant strides in medical technology today, with these techniques being used in almost every physical (biomedical) diagnosis. However, doctors still rely on 'natural' intelligence rather than 'machines' to diagnose psychiatric problems. Though AI and Machine Learning (ML) have proven effective in diagnosing physical illnesses, no machine created can yet accurately read a patient's mind.

AI has already been used for various diagnostic procedures related to psychosomatic or psychiatric conditions, especially brain imaging, mood rating scales, etc., to diagnose mental illnesses such as psychotic and depressive syndromes or to determine suicide risk.

II. WHY ARE MENTAL HEALTH PRACTITIONERS SLOWER TO ADOPT AI?

Psychotherapists are more patient-centred in their clinical practice, relying on 'soft skills' such as emotional connection and observation of behaviour. They are convinced that - at least today - the patient is more willing to discuss psychological problems directly with them than to respond to machines. That said, machines are also used in diagnosing psychological

disorders because they can detect behavioural patterns that a psychologist might miss.

AI can mimic human behavior, whereas ML constitutes a specific part of AI focusing on improving its abilities based on experience or data [3]. J. Gans defines AI as a program that identifies patterns and predicts the future based on this data [4].

Nowadays, millions of people live with mental disorders and their number is constantly increasing. Therefore, AI/ML has enormous potential, and holds great promise for compensating for the lack of qualified psychiatric personnel [5]. The following sections address these possibilities.

III. THE ROLE OF BIG DATA IN PSYCHOLOGICAL DIAGNOSTICS

AI and ML would be left powerless without Big Data, as these technologies rely on identifying certain habits. The Big Data sets include various psychometric information for determining and analysing psychological features to come to a conclusion. These sets include genomics, brain imaging data, blood biomarkers, cardiovascular, respiratory, and other biomedical patterns, mood rating scales, data from social media interactions, smartphone usage, speech and language, gaze patterns, facial data and other parameters such as shock responses.

IV. THE SCOPE OF AI/ML IN PSYCHOLOGICAL DIAGNOSTICS

One of the best examples of the use of machines in psychological diagnostics is the lie detector test. In this test, a person's bio- and psychomedical responses to certain questions are analysed. The machine is programmed to also detect behavioural changes in a person when they give wrong answers to simple questions. Some AI/ML applications that can revolutionise psychiatric diagnosis are:

- **Analyzing Voice Patterns:** AI/ML takes the lie detector concept further, using audio signal processing - when a person speaks, you can detect variations in tone of voice, pitch, energy level, and rhythm. Machines can help break down audio conversations into signals with thousands of unique characteristics [6].

Any change in mental health status can also lead to noticeable voice modulations. The psychiatrist may not

be able to detect subtle changes, but machines can. Moreover, machines can store huge amounts of data and classify it into certain categories depending on the voice pattern. AI algorithms can sift through huge amounts of data and make an accurate diagnosis when they come across a similar change in voice modulation. In this way, they can assist psychotherapists in accurately diagnosing behavioural patterns. For example, analysing voice modulations may prove useful in diagnosing depression [6]. The analysis of smartphone data holds great potential for identifying the mental state of patients. Smartphones can record enormous amounts of data. Therefore, any change in the data stream can help assess a patient's mental health status. Here are some examples of smartphone apps used by therapists to assess a patient's mental state:

a) **mindLAMP (Learn, Assess, Manage, and Prevent)**

The smartphone app mindLAMP is designed to ensure that therapist and patient agree on the data to be tracked, enabling its customization to the patient's mental health status. The idea is to create a user-specific digital phenotype to assess the patient's mental health status in real time, which might be helpful for high-risk individuals [7].

When tracking activity data, it has been shown that people with recurring patterns of activity and schedules in their daily lives show fewer mental health symptoms.

b) **BiAffect**

BiAffect is an app that uses ML in relation to keyboard activity. The algorithm takes into account activities such as typing speed, errors, backspace use, etc. to predict depressive episodes in patients with bipolar disorder [8].

Using activity sensors to monitor resting activity data and circadian timing helps detect possible depressive tendencies when used in conjunction with the BiAffect app [9].

Similarly, ML algorithms can be applied to social media and prove useful in detecting cognitive behaviour. For example, an algorithm was developed that scans Twitter profiles and content for evidence of suicidal intent and determines the suicide risk of users. This algorithm proved highly successful, with a hit rate of 88%, and assists psychiatrists and psychotherapists in screening their patients for suicide risk [10].

Similarly, AI could prove useful in scanning social media groups that deal with self-reporting of mental health problems [11].

- **Use of AI in MRI, EEG, and Kinesics Diagnosis:** Three long established 'biomedical' techniques in psychiatry are magnetic resonance imaging (MRI), electroencephalography (EEG) and movement diagnostics [12].

a) The most commonly used AI technologies used in neuroimaging studies and supporting MRI are convolutional neural networks (CNNs) and deep neural networks (DNNs). Recent innovations include 3D CNN

for extracting and detecting features of Alzheimer's disease and for detecting changes caused by the disease for MRI image analysis and recognition.

- b) EEG helps in the diagnosis and therapy guiding of brain diseases. Compared to MRI, EEG is a valuable research and diagnostic tool because it is suitable for studies that require millisecond temporal resolution. In addition, EEG provides results in the form of graphical data so that AI-based models can analyse them accurately. One of the latest applications is the Support Vector Mechanism (SVM) for more accurate identification of depression cases [13].
- c) Kinesics involves the analysis of behavioural, facial and other features to diagnose psychiatric disorders. For example, various algorithms have been developed to analyse facial expression profiles from video data to predict depression tendencies.

V. AI ALGORITHMS THAT COULD HELP IN PSYCHIATRIC DIAGNOSTICS

The various AI algorithms that could help in psychiatric diagnostics include Bayesian models, logistic regressions, decision trees, support vector machines, and deep learning [14].

VI. CONCLUSION

The clinical symptoms of psychiatric disorders can be diverse and complex. Therefore, they fall within the domain of machine learning. Moreover, machine learning techniques can help diagnose patients more accurately compared to the general medical system.

MRI, EEG and kinesics are important references for the diagnosis of psychiatric disorders. AI and ML might gradually eclipse traditional diagnostic tools in these procedures: Not only by improving the diagnostic efficiency, but also by enhancing the quality of the total diagnostic process through identifying trends that help prevent upcoming mental health problems.

AI is therefore likely to play an increasing role in assisting with diagnosis and in therapy guidance for psychosomatic and psychiatric clinical pictures.

However, working on where the opportunities lie must not overlook where the risks lie. These risks are likely to be found above all where the comparison with socially widespread and/or broadly accepted patterns leads to the person deviating in his behavior being seen as a disturbance and pathologized ("adjustment disorder").

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The Use of Artificial Intelligence and Machine Learning in Detecting Bipolar Disorder Symptoms

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Abstract—Technology has provided the world with the tools required to monitor physical abnormalities. Today’s emerging technologies, such as Artificial Intelligence (AI) and Machine Learning (ML), can help generate valuable data by monitoring and recording psychiatric behavioral changes, especially in patients with bipolar disorder. Smartphones can have dedicated apps that can trigger alarms when detecting changes in patients’ behavioral characteristics. These apps can generate reports and communicate with psychiatrists or emergency medical personnel in real-time to help them decide on the correct treatment procedures and medications for the patients.

Keywords: Bipolar Disorder, Artificial Intelligence, Machine Learning, psychiatric diagnosis

I. INTRODUCTION

Technology has advanced to such an extent that AI and ML have helped people get proper treatment on time in medical emergencies. One such example is the Apple Watch that monitors the user’s physical conditions through vital signs and other parameters. It alerts the emergency authorities on identifying abnormalities.

Another example is the Fitbit smartwatch. While being capable of collecting more diagnostic data than an Apple Watch, the Fitbit monitoring device is comparatively cheaper[1]

While AI and ML can be useful for detecting physical abnormalities, they can also identify psychological changes and detect mental ailments like bipolar disorder in advance. It can help people avail of treatment before matters go out of hand. This paper discusses AI and ML in smartphone apps to help detect abnormal psychiatric behavior associated with bipolar disorder.

II. HOW DEVICES SUCH AS SMARTWATCHES CAN HELP SAVE LIVES

A. Apple Watch

Apple CEO Tim Cook referred to the Apple Watch as the most personal device the establishment has ever created. There are many stories about how Apple Watch has helped save human lives. One such incident involving a 68-year-old teacher from Norway, Toralv Ostvang, occurred in February

2019. [2] Ostvang was spending the night with his friends just outside Oslo. He wanted to test a sleep app installed on his Apple watch. Hence, he wore his watch that night when he went to bed. Surprisingly, he discovered that he woke up in a hospital bed the following morning.

It transpired that he woke up at around 4 am and went to the bathroom. Suddenly, he experienced a drop in blood pressure and fell unconscious in the bathroom. Unfortunately, no one heard him fall. The collapse triggered the fall detection feature on his Apple Watch and notified the medical emergency services because it did not perceive any movement for one minute after the fall [2].

The local police contacted his wife and obtained his whereabouts. The paramedics admitted him to a nearby hospital, where they treated him for facial fractures. In a way, Apple Watch saved him from more serious complications by notifying the emergency medical services about the incident on time. Just as Apple Watch offers the technology to monitor physical parameters, smartphone apps can detect psychiatric behavioral changes and help patients with bipolar disorder [2].

Apple also provides Healthkit API for iOS app developers to access and make use of health and fitness data. It is essentially a central repository for health and fitness data collected through Apple’s smart wearables. Users would have to give permission to the app(s) that use this data. This dynamic data can be used in developing applications that can monitor mental disorders, such as bipolar disorder [3]

B. Fitbit Smart Monitoring Device

Fitbit smart monitoring device is similar to the Apple Watch, with the difference being that this device is compatible with the Android and iOS platforms.

One needs a Fitbit account to collect and assess Fitbit data. Generally, users can collect daily summary data that can be exported to an Excel or CSV file. Fitbit also provides a public web API for accessing Fitbit data. The highlight of this option is that it is free. One can also utilize a third-party platform for collecting Fitbit data. [1]

Compared to other similar devices, the Fitbit smartwatch appears to be a good option because it allows the collection of intra-day data. It can enable the psychiatrist to access and examine data in real-time, leading to quicker diagnosis, especially during emergencies [1]. The Fitbit smart monitoring device can collect the following data that could prove useful in diagnosing physical issues and psychiatric problems like bipolar disorder [4].

- Daily Readiness Score
- SPO2 and Health metrics
- ECG and Stress management
- 24/7 heart rate
- Sleep Tracking and Active Zone Minutes

Similar to Apple's Healthkit, Fitbit also provides public Web APIs that developers may use to retrieve Fitbit user data collected by Fitbit smart devices. It can then be used to create tools and applications to monitor mental disorders. [4]

III. WHAT IS BIPOLAR DISORDER AND ITS SYMPTOMS?

Bipolar disorder is a psychiatric condition faced by an individual, characterized by extreme mood swings ranging from emotional highs (mania) to lows (depression). So, when one experiences mania (or hypomania, a less intense form of mania), they feel highly energetic or euphoric, leading to unusually irritable behavior. And they lose the capacity to reason. On the other hand, they could experience depression, leading to disillusionment. Many people develop suicidal tendencies during such emotional stages, harming themselves [5].

Individuals can suffer from different variants of bipolar disorder. [6]

- **Bipolar I disorder:** In this variant, there is at least one manic episode preceded or succeeded by hypomania or depressive episodes.
- **Bipolar II disorder:** It involves at least one depressive episode and one hypomanic episode without having a manic episode.

Bipolar II disorder is a separate diagnosis altogether and not a milder form of bipolar I disorder. While bipolar I disorder cases can be severe, bipolar II disorder can keep patients depressed for extended periods causing significant impairment [6].

Though bipolar disorder does not have any definite cure, it can be treated by managing the symptoms using different methods, one of which is AI. Before discussing how AI can help handle the symptoms, here is a look at the list of symptoms [7]

- Mania and hypomania are different episodes but have similar symptoms [7]:
 - Enhanced activity and being restlessly energetic
 - Being abnormally jumpy

- Euphoric feeling and an exaggerated sense of well-being
- Unusual talkativeness
- Insomnia
- Distraction and racing thoughts coupled with poor decision making
- Depressive episodes are at the other end of the spectrum, manifested as listed below [7].
 - Feeling of depression
 - Loss of interest in routine activities
 - Loss of energy, or feeling tired
 - Exhibiting suicidal tendencies
 - Insomnia or excessive sleeping
 - Restlessness or unusually subdued behavior
 - Inability to reason and make decisions
 - Feeling of worthlessness

IV. HOW CAN AI HELP MANAGE BIPOLAR DISORDER SYMPTOMS?

A brief look at the list of the bipolar disorder symptoms will show that there are physical and psychiatric ones. The earlier Apple Watch example already depicted how physical symptoms can be monitored. Similarly, AI principles (applied through a smartphone) can help identify and monitor psychiatric symptoms associated with bipolar disorder, such as depressive and manic phases, and perform many associated functions, as described below [8].

- **Identifying mood swings through changes in speech patterns:** One of the primary symptoms of bipolar disorder is extreme mood swings from absolute depression to excessive euphoria. These mood swings bring about changes in the individual's speech patterns, affecting the speech volume, pitch, tone, and speed. AI can recognize these changes as they occur and warn bipolar disorder patients immediately that a mood swing is around the corner. It can trigger a voice alert or an alarm indicating that the patient needs to calm down soon. Otherwise, they might have to seek medical attention. AI can also help send a rapid report to a pre-programmed emergency contact number of the patient's doctor or a close relative who can help [8].
- **Monitoring sleep patterns:** The smartphone app can monitor sleep patterns and detect awake and active hours. Generally, the pulse rates go down when the person is at rest. Thus, AI can track the difference in the pulse rates when awake and asleep to send immediate notifications to an emergency number if there is a marked change in the patient's sleep behavior. Besides, it can trigger an alarm indicating the changes noticed in the sleeping patterns [8].
- **Maintaining a detailed calendar of activities and patterns:** Besides alerting the patient and the emergency authorities, AI can help keep a statistical record of each variation in the form of a detailed calendar. It can help the patient and the doctor to understand the extent of mood

swings, changes in sleeping schedules, and speech pattern variations throughout a calendar month. Accordingly, the doctor can suggest preventive measures or treatment. A mere glance at the app's statistical details will provide the doctor with a complete picture without the patient uttering anything [8].

- **Presenting information in the form of configurable graphs:** Just as AI helps maintain a calendar of activities, it can plot tracking points on a configurable graph to help patients analyze the changes in their behavior. This data can prove helpful to doctors and assist in prescribing proper medication. Bipolar disorder involves mood swings that can occur suddenly. It would be challenging for the patient to remember the exact time of the mood swings or explain the changes correctly to the psychiatrist. The data presented in the graphs show an accurate account of the events that helps the doctor take corrective measures [8].
- **Emailing reports directly to doctors and patients:** The smartphone app can be programmed to send monthly email reports to the psychotherapist besides the patient and their family members. This data can be subjective and in the form of online charts that can help them understand the gravity of the problem. Besides the monthly reports, the apps can send emergency reports and notifications if it detects excessively abnormal behavior. Thus, the psychotherapist can take immediate action and prescribe medication accordingly [8].
- **Tracking medications and reminding the user from time to time:** Another practical AI application is tracking the medicines prescribed by the psychiatrist and consumed by the patient. One can program the app to trigger alarms reminding the patient to take the required drugs. Besides, it can track the overall usage and help the patient order replenishments when the medicines get exhausted [8].
- **Monitoring changes in the individual's body depending on weather conditions:** The smartphone app can be synchronized and integrated with the local weather, daylight, and lunar phases to help patients visualize how these external influences affect their moods and trigger bipolar disorder bouts. These insights can prove helpful to patients and doctors alike [8].
- **Interacting with other patients with similar health issues:** It is possible to integrate the smartphone app with social media accounts and help the patients communicate with other patients and share experiences. At the same time, one can program the app to maintain data privacy by linking the patient's data within a members-only forum [8].

V. HOW CAN ML HELP MANAGE BIPOLAR DISORDER SYMPTOMS?

AI can generate vast amounts of data that patients and doctors could find challenging to comprehend and analyze. Machine Learning can help in solving the issue. Tools can be

developed to help analyze the enormous collection of data and assist the psychiatrist in making informed decisions.

VI. CHALLENGES IN USING AI IN TRACKING BIPOLAR DISORDER SYMPTOMS

Using AI to track bipolar disorder symptoms has its challenges. Below listed are some of the significant ones

- **Generating base data:** AI can help the app detect mood swings and plot data accordingly. However, it needs base data for comparison, developing which is crucial and the most challenging. The base data represents the figures when the patient behaves normally [8].
- **Proper patient education:** While AI can help the app generate data automatically, it requires the patient to use it correctly. Hence, the patients need to be educated and trained to manage the smartphone app appropriately. For instance, the patient might have to wear the sensors or carry the smartphone with them all the time to help the app generate accurate data [8].
- **Errors in diagnosing bipolar disorder:** There are chances of classifying bipolar disorder wrongly as depression or other psychological disorders. However, proper usage of the app can reduce these errors considerably. The psychiatrist or psychotherapist relies on the data generated by the app. Hence, it is the patient's or the caretaker's responsibility to use the app and help diagnose bipolar disorder correctly [8].

VII. CONCLUSION

Psychiatric problems like bipolar disorder require constant monitoring of various parameters. The data generated from these parameters needs comparison with the standard data to understand the variations and analyze them. Specialized smartphone apps can help monitor multiple parameters like speech variations, sleep patterns, and other behavioral changes to generate data that psychiatrists can analyze to prescribe medications or determine treatment. The data can also help patients understand the variations and seek medical attention immediately. Thus, AI and ML have tremendous scope in detecting psychiatric problems like bipolar disorder and taking prompt corrective actions

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Emerging Non-Volatile Memory for Smart Medical Devices

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Abstract—Wearable medical devices for the analysis of human vital signals should be as energy efficient as possible to ensure a long runtime on one battery charge. However, they have an inherent problem: the data rate of the signals to be processed is very low and the processing units have a very low duty cycle. A solution to this problem can be the use of emerging non-volatile memories and the introduction of a power-down mode. We present mathematical equations that help to evaluate when such an approach is beneficial. We also show how such a system can be designed in principle. Furthermore, a wearable ECG evaluation system is used to demonstrate the energy saving potential of such an approach at a real application. The result is a system which only consumes 0.98 mW of power on average.

I. INTRODUCTION

In recent years, the demand for small, embedded connected devices in the context of the Internet of Things (IOT) has continued to grow [1]. This trend is also evident in medical technology. So-called smart wearable devices can be put on by people in various forms. They can be integrated into clothing, smartwatches, or worn as a dedicated device. Wearable devices make it possible to easily measure and monitor vital signals such as heartbeat, body temperature, blood pressure or blood sugar levels.

Many hurdles still need to be overcome to enable the easy use of such devices. Besides optimizing the flexibility and size of the devices, one of them is the energy supply. Basically, two methods can be used: batteries and energy harvesting. Using energy harvesting allows for a high degree of flexibility, as the device does not have to be put down and recharged at regular intervals. However, using energy harvesting means an unstable energy supply and an unreliable system. To combat this limitation, non-volatile processors have been used, which maintain their internal state even without a power supply. They can therefore be put into a power-down mode as soon as the energy supply collapses [2].

We propose to apply this idea also to wearable devices with battery supply. Here, the energy supply is reliable over the entire period in which the battery is charged, but a different problem can be solved: Due to low frequencies of the human vital signals, sampling frequencies in the low 100 Hz range are often used [3]. Therefore, an evaluation algorithm executed on such a platform often has a low duty cycle. In this case it may be useful to first collect the sampled data in a buffer and then

process it in a burst. If a processing unit with integrated non-volatile memory is used for the execution of the algorithm, it can be put into a power-down state during data collection to save a massive amount of energy. This can drastically extend the operating time for such a wearable device with one battery charge.

Emerging non-volatile memory technologies seem to be very well suited for such an application. In addition to non-volatility, they often have other advantages, such as higher storage density, lower energy requirements or higher access speed [4].

In the following, we will discuss how such wearable medical devices with emerging non-volatile memory can be designed and what needs to be considered to achieve the lowest possible energy consumption and thus a long runtime.

II. TRADE-OFF ANALYSIS

The basic functionality of wearable devices with integrated evaluation is similar for any type of vital signal that is monitored. Figure 1 a) shows the functional blocks of such a device. A sensor detects the signal to be evaluated from the body. With the help of an AD converter, the signal is transferred to the digital domain. Preprocessing of the signal is then performed. For example, unwanted frequencies are filtered out. The actual processing and evaluation of the signal takes place after that. The result of this evaluation is usually stored on a storage device such as flash memory. The system design of a chip for a wearable device classically consists of one power domain and one clock domain. All the functional blocks reside in this power domain and are constantly powered during the runtime. Static and dynamic power dissipation therefore incurs for all functional blocks over the entire operating time.

A mathematical description of the energy consumption of a functional block is given in (1). E_x describes the total energy required by the respective functional block x to perform an evaluation of one result. Simplified, this total energy results from two components: the dynamic ($P_{x,dynamic}$) and the static power dissipation ($P_{x,static}$) integrated over time. D is the duration for which the functional unit is supplied with power. In a classical approach without any power-down mode, this corresponds to the total evaluation time T_{comp} .

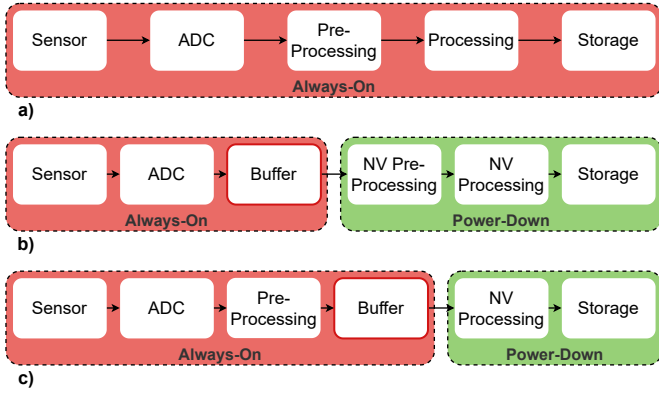


Fig. 1. Block diagram of a wearable medical device. a) Classical approach using one power domain without power-down and non-volatile processing. b) Our approach using two power domains, a buffer and non-volatile processing. Data is buffered before preprocessing. c) Our approach using two power domains. Data is buffered after preprocessing, benefiting from a data rate reduction during preprocessing.

$$E_x = \int_D P_{x,dynamic} dt + \int_D P_{x,static} dt \quad (1)$$

Our system design approach introduces a second clock and power domain. In addition, a buffer memory for collecting the measured values and a processing unit with non-volatile integrated memory are used. With this approach, the power supply of the second power domain can be disconnected during data acquisition and thus no dynamic or static power dissipation is incurred for all functional blocks in this domain. The system can be implemented in two ways: Approach 1 is shown in Figure 1 b). Here, the preprocessing unit uses non-volatile memory and is located in the *power-down* domain. In this case, the energy for the buffer storage ($E_{buffer,1}$) and the preprocessing ($E_{preproc,1}$) can be calculated as in (2) and (3).

Here $P_{br,dynamic}$ describes the dynamic power dissipation for storing the raw data from the sensor in the buffer. $P_{br,static}$ is the static power dissipation of a buffer that can hold as much raw data as is needed for one evaluation. $P_{br,dynamic}$ and $P_{br,static}$ accrue over the entire evaluation period T_{comp} , since the buffer resides in the *always-on* power domain. $P_{ppnv,dynamic}$ and $P_{ppnv,static}$ describe the dynamic power dissipation and static power dissipation of the preprocessing unit using non-volatile memories. Both only occur during the on-time (T_{proc}) of the *power-down* domain.

$$E_{buffer,1} = \int_{T_{comp}} P_{br,dynamic} dt + \int_{T_{comp}} P_{br,static} dt \quad (2)$$

$$E_{preproc,1} = \int_{T_{proc}} P_{ppnv,dynamic} dt + \int_{T_{proc}} P_{ppnv,static} dt \quad (3)$$

Approach 2 is shown in Figure 1 c). Here the preprocessing of the raw data is done during the data acquisition process

and before the data is saved in the buffer. Both buffer and preprocessing unit reside in the *always-on* power domain. Therefore, the energy consumption for buffer ($E_{buffer,2}$) and preprocessing ($E_{preproc,2}$) can be calculated as in (4) and (5).

The dynamic ($P_{pp,dynamic}$) and static power dissipation ($P_{pp,static}$) of the preprocessing unit occur over the entire calculation time (T_{comp}). On the other hand, the dynamic ($P_{bp,dynamic}$) and static power dissipation ($P_{bp,static}$) of the buffer can be significantly lower. This is especially the case if a large amount of data can be saved by the preprocessing unit (lower $P_{bp,static}$), for example by downsampling or quantization. It is also the case if many high-frequency components are filtered out of the input signal by the preprocessing unit (lower $P_{bp,dynamic}$). Depending on which sum of the two energies ($E_{buffer,1} + E_{preproc,1}$ or $E_{buffer,2} + E_{preproc,2}$) is lower, a decision should be made for approach 1 or approach 2.

$$E_{buffer,2} = \int_{T_{comp}} P_{bp,dynamic} dt + \int_{T_{comp}} P_{bp,static} dt \quad (4)$$

$$E_{preproc,2} = \int_{T_{comp}} P_{pp,dynamic} dt + \int_{T_{comp}} P_{pp,static} dt \quad (5)$$

The same calculations can be performed for all functional blocks of the system. Our system design approach will yield lower overall energy consumption, when the duty cycle of the processing unit is very low. In this case, it can be put into *power-down* mode for a relatively long time, thus saving a lot of energy. This saving then exceeds the cost of introducing a buffer. Because of low power requirements of emerging non-volatile memory, it can be assumed that a processing unit with non-volatile memory does not require more power than a processing unit with classic volatile memory ($P_{p,dynamic} \geq P_{pnv,dynamic}$ and $P_{p,static} \geq P_{pnv,static}$) [4]. Mathematically, a comparison between classical and non-volatile approach can be described as in (6), (7) and (8).

$$E_{proc,cl} = \int_{T_{comp}} P_{p,dynamic} dt + \int_{T_{comp}} P_{p,static} dt \quad (6)$$

$$E_{proc,nv} = \int_{T_{proc}} P_{pnv,dynamic} dt + \int_{T_{proc}} P_{pnv,static} dt \quad (7)$$

$$E_{buffer} = \int_{T_{comp}} P_{bp,dynamic} dt + \int_{T_{comp}} P_{bp,static} dt \quad (8)$$

Here $E_{proc,cl}$ denotes the energy required by the processing unit in a classical system. The activation time of the component extends over the entire evaluation time T_{comp} . For the non-volatile approach, two energy values have to be considered: the energy of the non-volatile processing system ($E_{proc,nv}$) and the energy of the newly introduced buffer memory (E_{buffer}). Here, the power of the buffer is incurred

over the entire evaluation time T_{comp} , but the power of the processing unit is incurred only for the power-on time of the *power-down* domain (T_{proc}). Energy savings with a non-volatile approach can always be achieved if (9) holds.

$$E_{proc,cl} > (E_{proc,nv} + E_{buffer}) \quad (9)$$

This evaluation of the power consumption of different approaches can be performed at different stages in the design process of such a system. In other words, the power values ($P_{x,dynamic}$ and $P_{x,static}$) can be obtained in different ways. With an energy annotated high level simulation at the beginning of the design process, a rough estimation can be made before any hardware needs to be implemented. While the accuracy of this approach is not very high, this can already be a very good indicator of which approach should be pursued further. The implementation of the approaches and power estimation on RTL level or after physical layout of the system can provide more accurate results, but requires greater effort. The most accurate results can be obtained by manufacturing an ASIC of the whole system and measuring real values. However, due to the high design effort, it is advisable to perform reference measurements on real systems once and then use them to create an energy annotated simulation.

III. CASE STUDY

To test our approach, we apply it to a design of a smart wearable system for ECG evaluation. ECG systems record the heartbeat through electrodes on the human skin. The measured signal is in the range of 0.01 Hz to 250 Hz [3]. Sampling rates of up to 512 Hz are therefore typical. Such a system has an average power consumption of about 35 mW [3]. Using our approach, we designed a system that first collects a few seconds of ECG data (*window*) and then checks for atrial fibrillation in a single run.

The evaluation is carried out with the help of a neural network. The processing unit uses non-volatile Resistive Random Access Memory (RRAM) as internal memory. This has the additional advantage that several states can be stored in one cell. A more detailed description of the internal memory block used can be found in [5]. The framework used for the design process is described in [6]. This system was implemented and a layout for an ASIC was created. Power consumption values were taken from a hardware simulation of the chip.

A schematic of the dataflow at different points of the design can be seen in Figure 2. The design uses approach 1 and thus the preprocessing is part of the data collection process. The sensor and the preprocessing unit operate at a frequency of 512 Hz. The clock frequency of the processing unit is 70 kHz. The *power-down* domain on-time ($T_{proc} \approx 25 ms$) per evaluation is only 0.2% of the total evaluation time ($T_{comp} \approx 12.6 s$). This results in an energy of $E_g = 12.4 mJ$ per evaluation. Compared to a permanent on-time of the *power-down* domain ($T_{proc} = T_{comp}$), approximately 95% of energy can be saved. For our wearable ECG system, the overall average power consumption per evaluation is 0.98 mW.

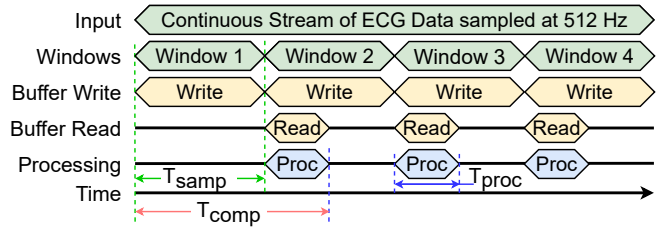


Fig. 2. Schematic dataflow of a wearable medical device for Afib detection in ECG data using non-volatile memory. The activation at certain points in the design are shown in the diagram. The activity of the sensor is shown as *Input*, which is divided into windows. The read and write operations to and from the buffer as well as the evaluation (*Processing*) are also depicted.

Compared to another solution from literature which needs 35 mW, our approach only needs about 3% of that [3].

IV. CONCLUSION AND OUTLOOK

We assumed that by incorporating emerging non-volatile memory into battery-powered smart wearable medical devices, the problem of low data rates and low duty cycles of the processing units can be solved. This can save a great deal of energy, thereby massively extending the runtime of such devices on a single battery charge. We have established equations that show under which conditions the use of such memory devices can lead to an advantage and what the principal design possibilities are. Using a system for ECG evaluation as an example, we have shown that the postulated significant savings can be realized in practice. On this basis, further medical applications can be investigated, where such an approach could be beneficial.

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