Neuroband: An Emotion Monitoring Smartwatch for Children with Autism

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Declaration and Approval

I declare that this project documentation has not been submitted to Strathmore University or any other University for the award of a Degree in Bachelor of Science in Informatics and Computer Science or any other Degree. To my knowledge and belief, the research document contains no material previously published or written by another person except where due reference is made in the research proposal itself.

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Abstract

Children with autism frequently face challenges in identifying and articulating their feelings, this hinders their social interactions and overall development. Outbursts, anxiety and withdrawal resulting from emotional miscommunication make it difficult for caregivers to provide support and meaningful intervention. Constant observation is therefore relied upon to track the child's behaviour, but this is often impractical for parents and caregivers. As a result, there is a growing need for innovative and proactive solutions to benefit both the parent and the child in supporting emotional development.

Although these assistive technologies exist, many fall short of addressing the full spectrum of their needs. Majority focus on providing tools for parents and caregivers while neglecting the child's active participation in learning emotion recognition. This ultimately makes children with autism struggle recognizing and regulating emotions independently.

The Neuroband system introduces a smart wearable device integrated with sensors to monitor physiological signals such as heart rate, body movement and temperature, to derive their emotional states. The system leveraged machine learning techniques to analyse the sensor data and display the emotional state to the child on the wearable device and to the parents through a mobile application. Following the Rapid Application Development, the system was tested iteratively to create a prototype that continuously updates the parent and child about the interpreted sensor data.

The choice of a wearable device is justified by its comparatively non-intrusive design, portability and ability to function continuously without disrupting daily activities. Children can then easily go about their daily routines as well as be monitored and gain immediate assistance. This is expected to empower caregivers with actionable information, helping them understand behavioural patterns and strengthen their ability to respond appropriately.

Keywords: *Autism, Children, Emotion Recognition, Wearable Device, Sensors, Monitoring, Machine Learning, IoT*

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List of Abbreviations

ASD	Autism Spectrum Disorder
GSM	Global System for Mobile Communication
CREMA-D	Crowd-sourced Emotional Multimodal Actors Dataset
WESAD	Wearable Stress and Affect Detection
GPRS	General Packet Radio Service

Chapter 1: Introduction

1.1 Background Information

Autism Spectrum Disorder (ASD) is a neurological disability depicted by difficulties with social relations or emotion regulation accompanied by unique restricted interests and repetitive behaviors. It is characterized by a wide variation in the severity of signs, diagnostics and level of support needed among persons with the condition (Shaw et al., 2025). Behavioural challenges are usually detected during early childhood with the presence of symptoms like sensory and auditory abnormalities, food selectivity, difficulty with eye contact, delayed speech and distress over small changes (Inal-Kaleli, Dogan, Kose, & Bora, 2025). Additionally, autism involves poorer facial and emotion recognition which impairs the ability to decipher important information regarding the emotional state of others (Yeung, 2022). This often makes autistic individuals struggle to form meaningful friendships and conversations because they fail to understand context through emotional cues. Another defining trait in autism is wandering or running away from caregivers, a behaviour referred to as elopement. This involves leaving home unexpectedly, even at night or in crowded places. This can put the child at risk and often cause significant anxiety or stress for parents (Scheithauer et al., 2025).

ASD is not entirely curable, but early diagnosis is desirable to allow early treatment and to improve the person's overall quality of life. Diagnosing ASD heavily relies on the clinical observation of behaviours that meet the standards set out in the Diagnostic and Statistical Manual of Mental Disorders (DSM) and the International Classification of Diseases (ICD). Tools used in the assessment of autism involve direct observational tests and interviews held with parents or caregivers (Fulceri et al., 2025). While the exact cause of ASD remains unknown, it is linked to a combination of biological, genetic and environmental risk factors such as alcohol consumption, older parental age and prenatal illnesses (Baloyi et al., 2024). Early identification of autism can enhance understanding of an individual's condition, which, in turn, helps families more informed decisions.

Families coping with autism often utilize complex measures to accommodate the needs of the affected individual. The responsibility of caring for someone with ASD can impact family relationships and the mental health of both primary and secondary caregivers, causing chronic stress, anxiety, and hypertension. In nations like the USA, the lifetime cost of treating an individual with ASD is estimated to range between \$2.5 and 3.5\$ million dollars per family, whereas in Africa, limited available resources as well as low income simply exacerbate the situation (Baloyi et al., 2024). This ultimately contributes to the stress and isolation of the family. Parents may also experience a period of grief over unfulfilled expectations and feel isolated due to limited support from those around them (Amate & Luque, 2024). Such grief may originate from an altered perception of the child's developmental and functional capabilities, leading the parents to commit to providing lifelong care for their child. Psychological intervention for caregivers has proven to be effective in providing emotional support caused by stress and feelings of isolation (Amate & Luque, 2024)

The standard for ASD diagnosis has evolved to take a modern approach, where classification methods of machine learning, including support vector machine, decision trees and k-means, are used to predict the severity of this condition. This also includes using wearable sensors for motion detection integrated with artificial intelligence to observe their interaction with the world (Simeoli et al., 2024). Assistive technologies like Augmentative and Alternative Communications (AAC), offer and alternative method to allow autistic individuals to communicate thereby reducing frustration. It has been used to support learning, mental health as well as interpersonal relationships among their peers. From a future perspective, Simeoli et al. (2024) discusses that artificial intelligence could greatly contribute to yield assistive real-time solutions to offer targeted support.

1.2 Problem Statement

While there are a variety of therapies and solutions available to support children with ASD, many are either resource intensive, costly or inaccessible to families, thereby limiting the ways they can respond to their children's needs in real-time (Gonçalves & Monteiro, 2023). Therapy sessions and interventions rely heavily on human interpretation and continuous professional involvement, specialized training and structured clinical settings. This is impractical and unhelpful in assisting parents and guardians to capture emotional shifts of the autistic child. Caregivers are left using limited monitoring tools to respond to children's emotional changes in real-time outside the therapy room.

Solutions such as visual aids and facial recognition systems incorporate trackers, lenses and sensors accompanied by artificial intelligence to identify emotional states in individuals with autism. These systems often use image processing algorithms which are affected by the need for constant calibration, environmental sensitivity and misinterpretations of gaze patterns, resulting in inaccurate emotional assessments (Gao et al., 2024). Furthermore, many of these systems rely on cameras and constant observation, also raising privacy and ethical concerns.

Since many of these tools often focus on providing feedback to the caregivers rather than to the children themselves, autistic children have limited opportunities to learn emotional self-awareness and development. The dynamic and unstructured environments the children often dwell in conflict with the requirements of many assistive technologies, making them less suitable for daily use and hinder their acceptance by families seeking discreet child-friendly solutions.

Ultimately, the absence of affordable and context-aware emotional monitoring tools for children with ASD represents a significant gap in both healthcare technology and everyday caregiving. The Neuroband system seeks to address this by designing a wearable device that combines physiological sensing, wireless connectivity and intelligent data processing to improve the overall well-being of autistic children.

1.3 Objectives

1.3.1 General Objective

To develop a smart wearable device that supports children with autism by continuously monitoring their emotional and physiological states and providing real- time feedback to caregivers through a connected mobile application.

1.3.2 Specific Objectives

i. To discuss how emotional states are currently monitored in autistic children.
ii. To determine whether emotion recognition can be taught or improved in autistic children through technology.
iii. To develop an android application and prototype of the wearable device that forms the interface for all the users of the system.
iv. To evaluate the system's performance in terms of accuracy, responsiveness and latency.

1.3.3 Research Questions

i. What are the current methods used to monitor emotional distress in autistic children?
ii. How can technology assist in improving emotion recognition in autistic children?
iii. How can an IoT system improve monitoring and emotional recognition for autistic children?
iv. How effective is wearable technology in detecting and reporting real-time emotional changes in autistic children?

1.4 Justification

The Neuroband system aims to benefit a wide range of users, each gaining advantages from its features and functionality. Paired with the advancements on the Internet of Things (IoT), this system continuously monitored physiological signals to provide timely support for the autistic. The system encourages emotional awareness and supports their integration into society while minimizing the risk of sensory overload. Gaining emotional awareness will not only improve the mental health of the autistic, but it will also allow their parents or caregivers to provide timely intervention when necessary.

Instead of using visual software which might raise privacy concerns, physiological-based systems are better alternatives due to their less invasive nature and ability to capture data without requiring visual engagement. Parameters such as heart rate, body temperature and movement patterns can provide valuable insights into a child's emotional state without requiring direct visual engagement. Combined with the convenience of wearable technology, this creates a more discreet, non-invasive and efficient approach that empowers caregivers to better understand autistic children. Passively collecting this data and transmitting it using mobile network technologies such as General Packet Radio Service (GPRS), allow caregivers to receive updates though a mobile application. This facilitates timely intervention and guidance from caregivers to subsequently teach the child to recognize their emotions and communicate in conventional manner. The implemented solution aimed to address destructive behavior and understand environmental triggers for personalized care, where professional assistance is not available.

At a societal level, schools contribute highly to shaping inclusivity in communities by providing support for children with various needs. Without these support systems, children will often struggle in social integration and simple communication. Generally, students with autism are more likely to be bullied and harassed by their peers than students with other identified neurological needs (Roberts & Webster, 2022). Such concerns leave many parents hesitant to allow their children to join these institutions and instead opt for home schooling. However, with the introduction of the proposed system, parents can remotely monitor their children and in return support their gradual integration into society. The system aims to alert these caregivers to rising stress levels, allowing intervention before extreme behaviors escalate. Teachers can then respond appropriately to tantrums without the stress of relying on verbal communication from the child. This helps them regulate classroom environments, teaching strategies and even sitting arrangements all in favor of the child. Integrating GPS functionality offers additional support for teachers to manage safety and supervision of students. Furthermore, GPS data can track wandering patterns and enable better planning for classroom layouts and playground supervision. Even for schools that already provide special education programs, this proposed solution supports behavioral assessments and emotional patterns for autistic children. This solution will allow schools to build trust with families and promote a supportive, safe learning environment for the children. Beyond the classroom, therapists and psychologists too can utilize the data collected to supplement clinical monitoring and serve as a useful tool in identifying behavioral trends and fine-tuning therapeutic approaches. The features of the proposed solution empower teachers and parents alike with peace of mind, enhancing their ability to ensure the child's safety and behavioral needs.

Ultimately, the impact of this system lies in its potential to improve the quality of life for autistic children by combining compassion, technology and inclusivity. The innovation of Neuroband strongly aligns with the United Nations Sustainable Development Goals, particularly Goal 3: Good Health and Well-being, as well as Goal 9: Industry, Innovation and Infrastructure, by leveraging wearable technology and data-driven solutions. These seventeen goals are a global appeal to provoke change in societal, economic and environmental dimensions (Serafini et al., 2022).

1.5 Scope and Limitations

1.5.1 Scope of the Project

As a solution, the system incorporated a smart wearable device specifically designed for real-time monitoring of autistic children through their physiological signals. Since caregivers often rely on traditional methods of monitoring, this method provided a simple approach to allow detection of emotional distress and immediate response. Catering for autism from infancy is critical and early intervention provides a crucial role in shaping their future development. Hence, the target population for this research and project comprises children and adolescents under the age of 35. While autistic adults beyond this age also face similar challenges, their needs are more complex and situational, requiring different and intricate strategies beyond the scope of this project.

Primarily, the wearable gadget was proposed to monitor physiological signs such as heart rate, electrodermal activity, temperature and analyse them through an emotion classification model. A General Packet Radio Service (GPRS) running on 2G cellular communication was used to allow the prototype to send sensor data to the cloud. Parents and caregivers were expected to set a mobile data plan for the device to be online when needed, to support functionality of the device. Through the mobile application, caregivers receive alerts and updates, which can be particularly useful where the child is exposed to hostility and other extreme situations in social settings. Additionally, the prototype displayed the identified emotion based on the sounds detected, as a means of teaching the individual the correlation between vocal tones and emotional states. As a supporting feature, with many autistic children wandering due to sensory overload or mere curiosity, a GPS location module was incorporated as well. This was to assist parents and caregivers alike to identify the child in situations where they could get hurt. All these features provided were supported by local storage and cloud support to provide real-time monitoring and analysis of the child's emotional state.

While the system aimed to support the needs of autistic children, the device is not intended to replace 24/7 clinical-grade monitoring systems. It also does not act as a diagnosis tool, therefore only aiding children already clinically labelled as autistic.

1.5.2 Limitations

The limitations of this project outlined the constraints and challenges encountered during the design and implementation of the Neuroband system. The limitations arose from factors such as hardware capabilities, data availability and time constraints. While every effort was made sure to ensure the system's reliability and functionality, certain aspects of performance, generalizability and scalability remain restricted. This section discusses these limitations, highlighting areas that may require refinement in future work.

Designing the prototype required precise placement of components to avoid electronic interference and to ensure that the size and performance are not compromised. This involved precise positioning of the heart rate, temperature and motion sensors as well as the GPS and GSM module. It is important to note that the GPS module requires a direct line-of-sight connection to satellites to receive radio signals showing location data. Obstacles such as buildings or indoor environment interfering with a clear view of the sky, resulted in reduced accuracy or loss of location tracking. Of equal importance was the comfort of the device and child-friendliness. Given the hypersensitivity of autistic individuals, special consideration was needed to guarantee comfort and adaptability to the device. Real-time processing also demanded software and hardware coordination, potentially impacting the battery life of the wearable device. Publicly available datasets for emotion recognition based on physiological signals are often limited, typically classifying less than five basic emotional states.

Additionally, the WESAD dataset employed in this study, is limited to just three emotional states, neutral, stress and amusement, which means that more complex emotions such as shame, confusion, or anger were not included in the labels and therefore could not be identified by the model.

1.5.3 Delimitations in the Project

The delimitations of this project outline the boundaries and scope intentionally set to ensure the scope of the project is focused and manageable. These choices define what the project includes, to provide an achievable framework while acknowledging areas that fall beyond its scope.

Only individuals formally diagnosed with ASD were considered as the primary target for this system, other neurodevelopmental conditions were considered beyond the scope of this study and thus excluded. The main pretension of the Neuroband system was to support parents and caregivers, therefore the system was designed primarily for use in social environments such as schools and play areas rather than in professional medical settings. Its users form individuals diagnosed with autism under the age of 35 years, to maintain practicality and focus on the target group of the system. Currently, the hardware architecture is limited to a wrist-worn device, though future work could explore alternative, less irritating wear locations. Albeit other data could have been incorporated to derive the child’s emotional state, such as visual or facial recognition methods, the system focused solely on their physiological signals to maintain simplicity and plausibility. Additionally, the use of GPRS was found to consume significantly more power than Bluetooth, which negatively impacted the device’s battery performance and longevity. The system has been designed for integration with a mobile dashboard for caregivers or parents and not as an independent standalone application for the autistic individual.

Chapter 2: Literature Review

2.1 Introduction

This chapter discusses the current body of knowledge related to emotional monitoring in autistic children, the role of physiological signals and integration of IoT in emotion recognition. Having understood the problems unique to autistic children, this section highlights how different researchers have used various techniques to create assistive technology using machine learning tools. Therefore, this literature review provides a foundation for identifying gaps that the proposed solution hopes to address.

2.2 Current Ways Emotional States Are Being Monitored in Autistic Children

The most frequently used method of monitoring children with any physiological condition is by behavioral observation. This involves monitoring the child's daily routine and natural interaction with their surrounding environment. A study performed by Wang et al. (2025), quantified methods of behavioral observation using computer vision for ASD treatment. This included a series of simple tests performed on autistic children to identify how their response correlates to their emotional states. The tests performed included the Expressing Needs with Pointing Test, in which children were tested on the use of gaze and gesture cohesion to show what they need. This returned positive results of 17/19 accuracy showing that although the children do not communicate verbally, simple observation can help prevent extreme behaviors. A caregiver may then assess the child's emotional state and react appropriately since this act of gesturing indicates willingness to seek help and be understood. Another test used is the Response to Name Test, for which shoulder and head posture were analyzed to gauge social awareness of the child. Autistic children were found to have longer reaction times, that would closely be linked to withdrawal or sensory overload. The researchers also concluded that delayed or no response could be due to heightened anxiety or stress levels. Meanwhile those that responded faster were notably calm and happy. The final test crafted was the Response to Instructions Test, which assessed the child's emotional capacity to cooperate during interactions. An autistic child who was quick to follow the instruction was likely to be in a calm state whereas hesitance or aggression indicated stress and discomfort. Collectively, these behavioural monitoring tests demonstrate that this approach offers a versatile and cost-effective means of interpreting a child's emotional state, enabling caregivers and clinicians to detect subtle feelings through observable actions and responses.

Medical partitioners take a more standardized approach by using questionnaires and interviews with parents to monitor the emotional state of the child. This method is mainly used as an assessment tool in diagnosing and determining the severity of the autism. The Aberrant Behaviour Checklist (ABC) is a worldwide rating questionnaire that contains 58 items under irritability, social withdrawal, noncompliance, inappropriate speech and stereotypic behaviour. It is assigned to a parent or any adult that has known the autistic child for a minimum of eight weeks and is expected to fill the questionnaire to provide a formal assessment of the child's psychological state (Farmer & Aman, 2021). This method is used to track the improvement of the child's social skills, awareness and emotion recognition as they grow older.

Physiological changes are also used to detect the emotional state using heart rate and electrodermal activity. Since stress and excitement can lead to a higher heart rate, while relaxed states show slower heartbeats, these physiological signals provide clear insight into the child's wellbeing. This technique also encompasses wearable devices that measure physiological activity to track sleeping patterns, speech support and repetitive behavior. Where the emotion of the child is not clear, this type of monitoring assists caregivers to recognize them and identify potential triggers.

2.3 Improving Emotion Recognition in Autistic Children Using Technology

In every learning process, technology has shown itself to be an invaluable asset. Ranging from interactive games to animations and complex machine learning techniques, emotion recognition has been made easier to detect through technology.

Interactive games are particularly famous among children for entertainment and learning purposes alike. When games are used for the sole purpose of learning while simultaneously exploiting their addictive nature, they are referred to as serious games (Garcia-Garcia et al., 2021). In the context of autism, serious games have been equipped with tangible user interfaces to detect emotions of characters and develop emotional awareness. These games aim to encourage children to practice expressing those emotions and allow them to independently identify what they mean. Pictures are often used in these games to relate facial expressions to emotions and teach the autistic children the correlation between the two. The research (Garcia-Garcia et al., 2021) carried out identified that the children enjoyed the game and wanted to continue playing even after their testing session was complete. This positive engagement indicates that serious games are indeed effective in teaching emotion-related concepts to autistic children.

Technology professionals identified that facial detection systems recognize faces in an image but also estimate the class of emotion based on facial traits. Real-time face emotion recognition is based on machine learning models taking into consideration the challenges that arise with facial recognition. These systems can be embedded in wearable devices or smart environments to help autistic children understand facial expressions. Unfortunately, such systems could easily misclassify emotions due to face images having different characteristics or simply faces indicating emotions different from their actual emotions (Talaat, 2023).

Educational robotics are also used to open new and promising prospects to the learning experience of autistic children. The research by Schiavo et al. (2024) discusses how social robots are equipped with artificial intelligence and ability to interact with humans to bring meaningful learning opportunities. Due to the integration of cameras, microphones, touch and motion sensors, these social robots are too considered a product of IoT. The robots collect data by reading facial expressions and mimicking the emotion to provide an appropriate response and interact with the autistic child. Examples of such robots are Nao, Kaspar, Robota and Milo (Ramachandran, 2022).

Virtual and augmented reality platforms also offer controlled environments where children can perform tasks or interact with characters to learn about emotions. This technology includes eye tracking, speech analysis and gesture tracking to inspect what elements of their environment they respond to. According to the research (Astafeva et al., 2024), immersive VR games in several trials led to improved communicative competence, better eye contact and social engagement among autistic children. In this study, engagement with avatars was expected, and the children impressively displayed prolonged eye contact and genuine interest in the conversations.

Wearable technology in the domain of IoT has increasingly facilitated the harnessing of intervention measures for children with ASD. This wearable technology can be classified into two functions signal acquisition and interactive feedback (Gao et al., 2024). Signal acquisition involves utilizing various sensors for real-time monitoring of physiological data. The interactive feedback system aims to decode psychological and behavioural challenges and identify the correlation between physiological data and emotion. The diversity of this technology has led to more unique solutions for ASD by the use of IoT including head-mounted displays (HMD), smart glasses, gloves and even wristbands. These devices all play a similar role in detecting emotions based on the child's physiological data. This technology applies a non-invasive and flexible method of monitoring that allows autistic children to lead a relatively normal social life without constant observational monitoring.

2.4 Related Works

Autism related assistive applications offer caregivers a modern and versatile approach to cater to individuals with ASD. These systems use evidence-based techniques to alert caregivers about the well-being of the child, as well as improve the child's capacity to verbally communicate.

2.4.1 Milo: The Humanoid Robot Enhancing Emotion Recognition in Autistic Children

Milo, a product developed by Robokind, represents a targeted solution for addressing the needs of autistic children through robotics and specialized curriculum. Designed to resemble a young boy, Milo stands at two feet tall and weighs 4.5 kilograms, making it accessible and non-intimidating for the target demographic. The bot was equipped with 1GB of RAM, OMAP 4460 dual-core processor and 8GB memory capacity. A 5-megapixel autofocus camera was installed in Milo's right eye to detect motion and facial recognition of the children, as shown in Figure 2.1. Milo allows connection to other devices through Wi-Fi and Bluetooth connectivity to display collected data.

Figure 2.1 Milo the Robot Engaging with An Autistic Child (Wiersema, 2023)

Milo is powered by the CompuCompassion system to prioritize social and emotional skills in conversation. The robot was intentionally developed to assist educators in interacting with the autistic children and cultivating emotional awareness. A successful 87.5% engagement rate among autistic children, showed a significantly higher responsiveness than when only a human therapist was present to engage with the child (Ramachandran, 2022). The unique interest in Milo the robot could be linked to its cartoon-like appearance that captures the attention of the children as shown in Figure 2.2, the personalized interactions they experienced or the robot's ability to make conversations less intimidating.

Figure 2.2 Milo the Robot's Cartoon-Like Appearance (Wiersema, 2023)

The overall assessment of the robot returned varying degrees of success in engaging children with ASD, through social interaction, simple games and continuous engagement. Milo was successful in initiating and creating the flow of conversation to encourage the children to be verbal.

2.4.2 Empatica E4 Wristband

The Empatica E4 Wristband is a wearable gadget intended for the detection of stress by monitoring physiological signals. Worn on the wrist, it collects physiological data, enabling an objective assessment of an individual's stress levels throughout daily activities. The physiological signals measured include Electrodermal Activity (EDA), Heart Rate (HR), Skin Temperature (ST) and Blood Volume Pulse (BVP) (Campanella et al., 2023). The E4 is equipped with multi-sensor capabilities and data storage with onboard memory storing up to sixty hours' worth of data. It also supports Bluetooth and USB 2.0 connections for data synchronization. It weighs 25 grams and has a battery life of up to 36 hours on a single charge. The wristband uses a cloud-based platform to connect to a mobile application to be used by the parents or caregivers and provide visualization of the data collected. Overall, it has a simple and sleek design as shown in Figure 2.3 and Figure 2.4.

Figure 2.3. The Empatica E4 Wristband Front View Design (Empatica, 2021)

Figure 2.4 Empatica E4 Wristband Back Design (Empatica, 2021)

Empatica's official guidelines encourage users to wear the wristband on their non dominant hand, this was attributed to the motion of dominant hand creating noise that affected data collection by the sensors. The intention was also to align the sensors with the area containing the greatest concentration of blood vessels for the best reading (Borghi et al., 2024). The watch-like design integrates seamlessly and does not hamper with the day-to-day activities of the autistic children.

Further testing indicated that the heart rate variability (HRV) decreased during stress but increased when the child was calm, implying a clear physiological response linked to emotional state (Campanella et al., 2023). This led the researchers to conclude that fluctuations in HRV implied the occurrence of challenging behavior like aggression, tantrums and self-injury. Therefore, the combination of wearable devices and physiological monitoring for the E4 has proven to provide valuable insights in understanding behavioural patterns of autistic children.

2.4.3 The Superpower Glass: A Prototype to Support Emotion Recognition in Children with Autism

This Superpower Glass presents a medical pair of glasses with inbuilt sensors for measuring physiological signals to help monitor health conditions, especially epilepsy. It utilizes computer vision to perform facial recognition and interpret their emotional expressions in real-time. The glasses performed tasks such as face recognition, animal and plant identification, basic knowledge of Quranic surahs, letter and number recognition. This facilitates the means to support the integration of autistic children into society by helping them be independent.

This smart glass can be referred to as a head-mounted display (HMD) system, capable of presenting information to the user in various ways (Elsherbini et al., 2023). It is equipped with an ESP32-CAM with Wi-Fi integration to allow video streaming and image processing using the OpenCV python library. It uses an LCD screen display to provide a high-resolution view, positioned at a 45-degree angle with a mirror for reflection. It uses a lithium battery that powers the device and provides the user with six hours of wear-time without the need for frequent charging. A fall sensor was also included using gravitational acceleration to alert parents and caregivers immediately through the mobile application. The prototype design of the smart glass is as shown in Figure 2.5.

Figure 2.5 Prototype of the smart glass (Elsherbini et al., 2023).

The system includes the use of a web and mobile application to visualize the data being recorded by the glasses. The sensors are displayed to the parents on the mobile application alongside their real-time readings.

The system also utilized the FPDF library to generate PDF reports that could be reviewed by a physician for further diagnosis and treatment. Using facial recognition, the smart glass also identifies the emotions relating to different expressions and aimed at enhancing the emotion recognition skills of the autistic child. Further testing showed a distinct change in behavior in the children even when not wearing the device, therefore improving social interaction and emotion recognition (Perry et al., 2024).

2.5 Gaps in the Existing Solutions

To better understand the unique potential of the proposed solution, a thorough view of the limitations of existing similar technologies was essential. Notably, these solutions discussed have utilized IoT using diverse methods such as facial recognition, auditory and sensory input, to support day-to-day living of these autistic children. In this section, the limitations of each solution in the everyday context are discussed.

The use of robotics appears promising and effective, however, there were technical limitations associated with its ability to cater to ASD. Milo's performance may vary significantly due to the range of symptoms that autistic children experience. Some children may find robots unhelpful and simply uncomfortable to interact with. Additionally, many were inclined to interact with Milo in a manner comparable to friendship, forming emotional attachments that could have led to unrealistic overreliance on robots for interaction, and in turn affecting interactions with humans (Ramachandran, 2022). Milo may also lack adaptability to a child's current emotional state. In the event of a tantrum, the robot would not be able to comprehend the situation since it operates primarily on pre-programmed lessons and algorithms. Since it is also not a mobile device, it is limited to a static environment which would reduce its applicability in day-to-day life. Lastly, Milo's advanced hardware, training and curriculum package make it one of the most expensive robots designed for autism intervention (Ahmad Qadeib Alban et al., 2023). The hefty price adds an element of unavailability and inequity in access to many parents seeking assistive technology for their children.

The E4 is a research grade wearable device known for its adaptability, accuracy and its efficient sensory capabilities. Its primary limitation however is its passive character. The device is not equipped with any user interface to display feedback to the child and show its purpose. The child is therefore presented with a dull, non-interactive wearable device that would appear unnecessary and lead them to remove or destroy the device. The device lacks child friendliness and design consideration to counteract potential resistance or inconsistent use. The absence of real-time interaction also made it less suitable outside a clinical context. In educational environments, a teacher would also need to access the mobile application to view the emotional state of the child. This adds an extra step to the usability and practicality of the device and poses the lack of interactivity as quite the disadvantage. Most importantly, while it collects the data accurately, it does not interpret emotional states, and thus leaves the parent or caregiver with large, recorded data that would be tedious to make sense of.

While the Superpower Glass Project represents a smart approach to wearable devices and use of computer vision, it is not without limitations. The system's nature relies heavily on the surrounding environment, and conditions like proper lighting and proximity for emotion recognition. This was perceived as problematic in real-world situations where lighting may vary, and rapid head movements could hinder the functionality of the device. In a world where autistic children are prone to avoid direct eye contact and visual engagement, the glasses could be less effective in encouraging eye contact. The real-time interpretation of facial expressions for such children may also be overwhelming and intrusive if presented too frequently. The glasses also do not account for the child's emotional state, only focusing on interpreting social cues from others. This inhibits the capacity to give exhaustive understanding of the child's emotional needs and experiences. In summary, although the smart glass shows great promise, more design elements are required to be considered to optimize child and autistic friendliness of the device.

2.6 Conceptual Framework

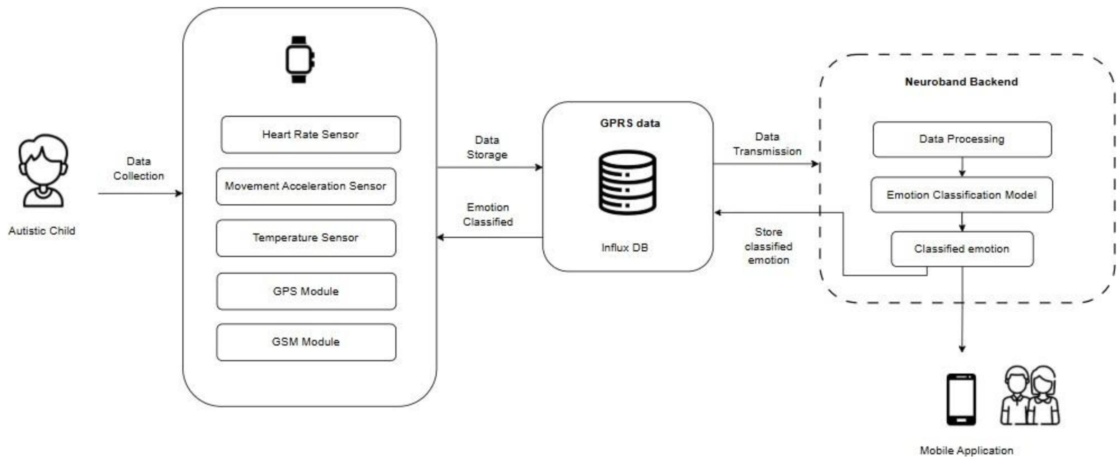

Figure 2.6 Conceptual Framework for the Proposed Solution

The Neuroband system is designed to support the emotional and physical well-being of autistic children by continuously monitoring key physiological and environmental stimuli. At the core of this system is a wearable device equipped with multiple sensors that collect real-time data. After complete analysis of this data, the system aimed at detecting anxiety, unidentified triggers and stress to give caregivers better understanding of what certain behaviors mean.

Data is expected to follow a series of processes and output useful information in contribution to autistic children's emotional awareness. The wearable device in this context was taken to be a smart watch and is expected be placed on the child's wrist, on the non-dominant hand. The inputs to be processed are collected through sensors and modules as illustrated in Figure 2.6. These record the heart rate, movement acceleration and temperature of the skin which will collectively be used to determine the emotional state of the child. This was expected to assist in providing quality insight into the child's emotional state. To cater for the symptoms of wandering and elopement, the GPS module was expected to collect coordinates of the watch to provide live location tracking to ensure safety of the child. The GSM module will be used to provide GPRS connectivity for the device by a sim card loaded with mobile data. Once the data was collected, it was transmitted via the GPRS network for storage on InfluxDB.

This step ensured that the device was not overloaded with local processing and large data which could affect responsivity and user experience. Upon storing, the data is then accessed by the

Flask Backend through RESTful API calls to clean, extract and organize it to be used by the emotion classification model. From the backend, this data is then loaded into the machine learning model to identify an emotion based on the physiological data. This model applied various training techniques to identify patterns and correlations that may correspond to specific emotional states like stress or anxiety.

After successful classification, the result was then recorded in the database and transmitted through the GPRS to be displayed on the prototype to the autistic child. The aim here was to make the child gradually learn how to identify and communicate their emotions. This constant display of classified emotion to the child was simultaneously shown to the mobile application. The parents are sent real-time updates that allow quick response in case of any distress or emergency. In the event of elopement, the device is expected to provide the live GPS location to the mobile application on the parent's end to facilitate efficient tracking and ensure quick recovery of the child.

Chapter 3: Development Methodology

3.1 Introduction

This chapter describes the software development methodology proposed for the system, to create a structured approach to ensure efficient design and implementation. The tools and techniques to be employed from prototyping to testing of the system are highlighted. Additionally, the research paradigm and major deliverables expected and relevant design illustrations detailing components of the system interaction are discussed with detail. This methodology is expected to ensure a scalable and flexible approach to designing the proposed solution.

3.2 Research Paradigm

This project adopted an experimental research paradigm aimed at validating the feasibility of the prototype in real-time emotion detection. Experimental approach involves manipulation of variables and testing the hypotheses to optimize performance of a model (Qiu et al., 2025). It was therefore appropriate because this study involved collecting physiological data and applying machine learning models to evaluate the results. The goal here was to determine whether the emotional states of a child can be reliably identified using biometric sensors and speech analysis. The approach is grounded in measurable outcomes and hypothesis testing, with clearly defined independent variables which were crucial to the implemented system.

3.2.1 Data Acquisition

Data used in this study was compiled from both external datasets and real-time sensor inputs. For the physiological data, the WESAD (Wearable Stress and Affect Detection) dataset was utilized. This publicly available dataset is specifically designed for wearable sensor-based research and includes multimodal data such as heart rate, temperature, electrodermal activity (EDA), and accelerometer readings. It has been widely used in studies involving emotion recognition, mental health monitoring, and stress detection. The WESAD dataset provided a strong foundation for training and validating the emotion recognition model used in this project.

3.2.2 Data Processing

This data processing phase involves converting raw sensor readings into structured, meaningful information that can be used to interpret the emotional state of the child. The process began with data cleaning, where missing inconsistent or noisy readings from the sensors are detected and removed to maintain accuracy and reliability. During feature extraction, key parameters such as average heart rate, acceleration magnitude, and movement intensity are derived. These features help identify correlations between physiological responses and emotional changes in the child. The extracted data is then standardized to ensure uniform measurement scales and consistent interpretation across different sessions.

Finally, the processed data is transmitted to the mobile application interface, where it was analysed and visualized for caregivers. This enables real-time monitoring of emotional variations and supports timely interventions to help the child regulate their emotional state.

3.2.3 Model Training

The model training phase focused on developing a reliable classifier capable of identifying emotional states from the processed physiological data. The Random Forest algorithm was selected for this task due to its robustness, ability to handle non-linear relationships, and effectiveness in reducing overfitting compared to single decision-tree models (Salman et al., 2024).

The pre-processed physiological signals from the WESAD dataset, including heart rate, temperature and accelerometer readings, were used as input features. These features represent the physiological changes associated with emotional states such as stress, amusement, and neutrality. Each record in the dataset was labelled according to its corresponding emotional category, allowing the model to learn patterns that distinguish one state from another. During training, the Random Forest algorithm constructed an ensemble of multiple decision trees, each trained on different subsets of the dataset. The final prediction for a given input was determined through a majority voting mechanism across all trees, improving classification accuracy and stability.

Key parameters such as the number of trees, maximum depth, and minimum samples per split were optimized to balance model performance and computational efficiency. The algorithm's ensemble nature also provided an inherent estimate of feature importance, helping to identify which physiological signals most strongly contributed to emotion classification.

3.2.4 Model Validation and Testing

After the model was trained, a validation and testing phase was conducted to assess its accuracy, reliability, and generalization ability. The goal was to ensure that the Random Forest model could accurately classify emotional states not only within the training data but also when exposed to new, unseen physiological data.

The dataset was divided into training and testing subsets using a standard split ratio to prevent data leakage and ensure independent evaluation. It involves using the validation results to gauge consistency of the model's predictions (Tor, 2024). The testing subset contained data samples that were not used during model training, allowing a fair assessment of performance. Model validation involved fine-tuning key hyperparameters such as the number of trees, maximum depth, and minimum leaf samples to achieve an optimal balance between accuracy and computational efficiency.

Performance evaluation was conducted using classification metrics including accuracy, precision, recall, and the F1-score, which provide a detailed understanding of how well the model distinguishes between emotional states. A confusion matrix was also generated to visualize the number of correctly and incorrectly classified instances across categories such as stress, amusement, and neutral states. The results demonstrated that the Random Forest classifier achieved consistent and stable performance across multiple validation rounds, confirming its robustness in handling the variability of physiological signals. However, slight misclassifications were observed between closely related emotional states, which could be attributed to overlapping physiological patterns among individuals.

Once trained and tested, the model was integrated into the system's backend to process incoming real-time sensor data and classify the child's emotional state. The output is then relayed to the mobile application, where caregivers can view updates and track emotional trends over time.

3.3 Software Development Methodology

Software development methodologies contribute to the planning, execution and delivery of a software system. They provide a structured blueprint that helps manage complexity, define deliverables and facilitate communication among stakeholders. In regard to an IoT based solution, hardware management, software development, mobile and cloud programming interfaces must be considered when selecting the software development methodology (Süren et al., 2022). Failure to which results in exploitation of vulnerabilities for the system and the consumer.

Given the nature of the proposed solution, the Rapid Application Development (RAD) methodology was selected to assist development of the system. RAD provides an iterative approach in development, shorter design stages and an emphasis on rapid development (Imam Riadi et al., 2024). A prototype is also formed to accommodate user's needs in the early stages making it better suited for the proposed solution. RAD highlights the boundaries of a system to ensure that it always prioritizes the end user's needs and high-quality result of the system. Additionally, RAD is open to suggested alterations even late in development by ensuring regular customer engagement throughout the development cycle (Beres, 2022). This reduces the risk of conflict and time wastage due to mismatched goals. In the proposed solution, the RAD methodology is expected to provide flexible and continuous testing of all functions and equipment. Its application to an IoT system is an advantage, as it supports rapid prototyping and repurposing of software compared to other methodologies (Nalendra, 2021).

The RAD methodology consists of the four stages that are shown in Figure 3.1.

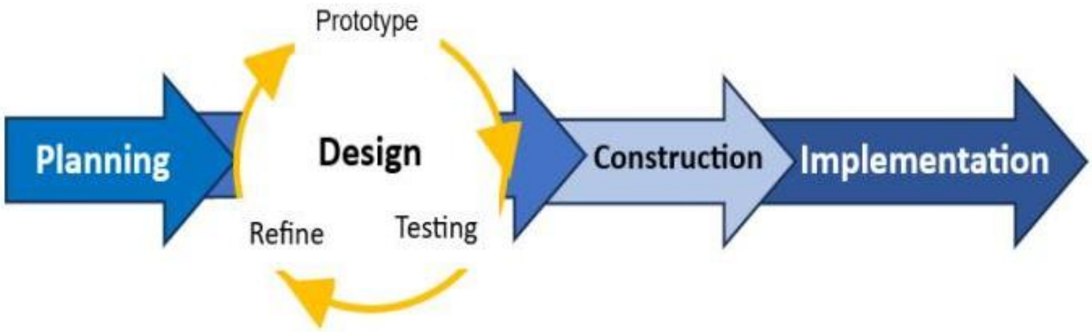

Figure 3.1 Stages of RAD (Imam Riadi et al., 2024)

3.3.1 Planning

This introductory stage involves identifying the system's functional and non-functional requirements. Input is gathered from key stakeholders to ensure the system performs its intended purpose correctly. During this phase, decisions are made regarding the timeline, phases of development and technologies to be used. In this system, features like emotion recognition, physiological monitoring and real-time updates formed the focal point of the design and technology to be used. Parents, caregivers and educators are expected to provide the relevant input regarding the functionality of the system. The goal here was to ensure that this stage forms the guideline for the development and prototyping of the system.

3.3.2 Design

This phase begins with creation of initial prototypes and system models. The objective here was to quickly develop functional prototypes of both the wearable device and mobile application that can be demonstrated to the parents and caregivers. The design was expected to reflect the user needs and expectations while performing optimally. Prototyping the wearable device encourages hands-on development and real-time testing to support active modification and updates. The prototype also allowed testing in realistic scenarios and identifying of design flaws, especially with reference to children. Furthermore, this phase helped assess the technical feasibility of integrating several complex components like the physiological sensors and algorithms. As a result, debugging efforts will began early in the development process and long-term errors were be addressed immediately.

Unit testing was also performed to test the program algorithms in an isolated manner from other parts of the system. The aim is to ensure that each method interacts seamlessly with the sensors in collecting data, transporting it and processing it accordingly (Imam Riadi et al., 2024). This supported error handling throughout the program and prevented system failure by displaying informative error messages and fallback pages.

3.3.3 Construction

During this phase the individual components of the system such as the heart rate monitor, microphone, GPS and GSM module were developed and tested using the Black box testing method. This method is commonly used in software testing to ensure that the system functions as intended by verifying that each component or feature performs correctly under specified test conditions (Engels et al., 2023). For Neuroband, the emotion detection module was tested with various physiological signals, and the expected output is compared to the actual output. Similarly, GPS inputs were tested to verify that the location of the child is displayed on the application correctly. The modules were validated independently and monitored for unexpected behaviour to be identified and corrected immediately. Once functional testing was complete, usability testing was performed to gauge performance of the device in real-world interactions. This is crucial particularly for the primary users, autistic children, who require a system that is reliable and intuitive.

3.3.4 Implementation

Here the fully tested and validated modules were deployed into a real operating environment. Since RAD emphasizes iteration and modular development, this phase benefits from the earlier phases of testing and refining. The core components, including the mobile application interface were combined into a unified functioning system. In RAD this often begins with involving a group of real users testing the system to assess its performance, this controlled testing helps identify unseen compatibility or usability issues (Engels et al., 2023). The backend components like cloud storage and physiological logs were deployed and tested further for reliability. Overall, the implementation phase is dynamic and crucial in ensuring the final product delivers meaningful support and improves the emotional wellbeing of the autistic child.

3.4 System Design Diagrams

3.4.1 Use Case Diagram

This diagram illustrates the different functionalities of the system from the user's perspective and identifies interactions between these entities (Rahman et al., 2021). It highlighted how the autistic child's behavior facilitates the functionality of the wearable device and how the system then detects emotional states and alerts parents. This served as a foundation for test case development.

3.4.2 Context Diagram

This is a high-level abstract illustration of a system. It represents a system as a single process and shows how it interacts with external entities to perform system functionalities (Malinova & Mendling, 2021). These external factors include the child, parent, cloud database and backend and the emotion classifying algorithm. This diagram helped with requirement gathering and scope determination.

3.4.3 Database Schema

The database schema acts as the blueprint of how the data is structured when stored. It includes tables, fields, data types and relationships between tables (Barzegar et al., 2021). It defined how sensor data, emotional state logs, GPS data and user profiles were stored, guaranteeing data consistency and retrieval efficiency. The tables included users, sensor readings, notifications and emotions detected.

3.4.4 Class Diagram

This diagram represents the system's object-oriented nature by illustrating it through classes, attributes, methods, and the relationships between them (Elov Botir Boltayevich et al., 2024). This was aimed at supporting the design and implementation of the system while prioritizing interaction and effective data management. The key classes included the notification system, an abstract sensor class, user entities, and the database.

3.4.5 Entity Relation Diagram

This refers to a visual representation used to describe entities, their attributes and their relationships with each other (Rashkovits & Lavy, 2021). The main entities for this solution were users, which include parents and the children with autism, alongside their attributes like name, gender, age which were recorded in the database. The diagram illustrates the use case flow from the point of data collection from the user, to uploading onto the cloud and syncing with the mobile application.

3.4.6 Wireframes

Wireframes serve as a blueprint for the user interface of a system. Here, the design elements were illustrated in the wireframes to show how the user is expected to navigate through the system. This guided the development of the interface and allowed early iterative redesigning to create a user-friendly system.

3.5 System Development Tools and Techniques

3.5.1 Arduino IDE

This is an open-source software used to compile and upload code to microcontrollers, making it a default platform for interactive hardware projects (Kondaveeti et al., 2021). It served as the environment for programming the handling of input from sensors and other components embedded in the smartwatch. It facilitated local processing of the data and transmission to InfluxDB for storage and further processing.

3.5.2 Flask

Flask is a lightweight and flexible Python framework used for building web applications. It has routing, Jinja2 templates and command-line integration making it flexible for developers to use (Bonney et al., 2022). For this solution, it was used to create a RESTful API to act as the middleware between the emotion classification model and the mobile application. It received the data from InfluxDB and fed it into the model to perform the classification and parse the data in a JSON format before sending it to the mobile application. This formed the framework for the backend of the Neuroband system, providing a lightweight and simple mode of communication between the devices, users and server.

3.5.3 InfluxDB

InfluxDB is an open-source time-series database designed specifically for storing, querying and analyzing time-stamped data. In this IoT based system, it was particularly useful to store continuous sensor data readings and verify device status over time. InfluxDB allowed ease of read and write of data, allowing the use of API calls to export and process the data for the emotion classification model. It also contains dashboards that were useful in visualization and tracking patterns within the collected data.

3.5.4 Firebase Database

Firebase is a real-time backend database that was developed by Google. It provides cloud storage, user authentication, tracking analytics and real-time database management (Trimbakrao et al., 2022). Firebase stored user and sensor data, allowing the mobile application and Flask backend to make API calls to further process this data. Firebase Auth also provided functional endpoints to allow users to update their passwords, change their email and sign in with Gmail.

3.5.5 Google Colab

This is a popular Google Research product that allows developers to write and execute code in sections and is especially used in machine learning and data analysis projects (Naik, 2023). In this project this environment was used to train and test the models used to classify emotions based on auditory and physiological data. Google Colab took on the workload that a computer would have been unable to handle especially when dealing with machine learning models.

3.5.6 Blynk

This is a platform designed to support the building and monitoring of IoT devices through a mobile application. It contains interface components where developers can drag and drop widgets to interact with their hardware. This platform is lightweight and has fast performance making it a good tool for effective monitoring (Shakib Sadat Shanto et al., 2023). The aim of using Blynk was to prototype the mobile application that is communicating with the wearable device. While it was primarily used for testing, it offered a fast and efficient way to visualize and interact with IoT data before building a complete application from scratch.

3.5.7 Black-box Testing

This is a software testing technique where internal logic or program of the application is unknown to the tester. The focus is mainly on input and monitoring the actual output against the expected output to identify potential biases and limitations (Wang, Zhang, et al., 2025). For the implemented solution, it was used to test the functionality of the wearable device and synchronization with the mobile application.

3.6 Deliverables

3.6.1 System Documentation

This documentation included detailed system specifications, formulas, design diagrams, testing and implementation procedures used in the development of the system. The document ensures ease of use, maintenance and further development of the proposed solution. It includes technical and non-technical aspects of the system useful for stakeholders and further research.

3.6.2 System Prototype

A comprehensive prototype demonstrating the practical implementation of the emotion detection was created. It included the GPS, GSM and sensor modules that were integrated into the device to analyze the emotional state of the child. GSM provided cellular data for internet connection of the wearable device to ensure the device is reliable and applicable in real-world scenarios. The GPS provided longitude and latitude data that were used to always ensure the safety of the child, and the sensors were used to collect the physiological data from the child.

3.6.3 Emotion Classification Model

This included integration and optimization of machine learning models to detect emotional states from physiological data. These models were trained using large, credible datasets to ensure high accuracy, reliability, and robustness in recognizing a wide range of emotional cues, thereby enabling timely and effective interventions.

3.6.4 Neuroband Mobile Application

The mobile application delivered a user-friendly interface for parents to monitor the real-time data of the autistic child. It also provided parents and caregivers with a comprehensive system to upload and modify their data, receive alerts on the child’s status, view reports, and monitor the location of the child. This application formed the core of user engagement and functionality of the Neuroband system, always ensuring that the wellbeing and state of the child is prioritized.

Chapter 4: System Analysis and Design

4.1 Introduction

This chapter provides the foundation for the development of the system by outlining its requirements, analysis and design components. It begins with the system requirements which define the behavior, constraints and quality standards. The system analysis models including use case diagrams that capture user interactions and data flow diagrams are also included in this chapter. Together these establish a clear framework that guides the system development process, ensuring both well-structured and user-centered development.

4.2 System Requirements

4.2.1 Functional Requirements

i. Profile Management - Parents/caregivers shall be allowed to create and update a basic profile, with details like name, age and gender. The aim is to ensure that profile information is properly maintained.
ii. Sensor Data Collection – The smartwatch shall measure and record physiological body signals which include, heart rate, GSR and skin conductance rate from the child. This data is then sent to the backend cloud network for classification by the machine learning algorithms.
iii. Data Visualization – The mobile application shall present the recorded readings in graphs and summaries (daily, weekly) to allow parents to easily monitor trends in their child's emotional state. The aim here would be to support medical partitioners in further diagnosis in case of consistent, intense emotions experienced by the child.
iv. Interpreted Insights with Machine Learning – Machine Learning models shall be used to analyze the stored data and provide simple insights. The insights will be accessible through the mobile application.
v. Data Storage – Data shall be collected and transmitted over the GSM cellular network to the cloud for remote access and further processing.

4.2.2 Non-functional Requirements

i. The Neuroband smartwatch shall process and transmit sensor data with minimal latency, this would be in the form of real-time or near real-time transmission.
ii. The system shall operate with over 90% uptime.
iii. The backend support shall ensure all data collected is encrypted and stored securely.

iv. The system shall allow only authorized personnel (parents/caregivers) to access a child’s data and view reports.
v. The mobile application provides an intuitive, user-friendly but practical interface for parents to use.
vi. The smart watch shall record heart rate readings with reasonable accuracy += 2 beats.

4.3 System Analysis

4.3.1 Use Case Diagram

This diagram presents the system’s behaviour from the perspective of its users, providing a structured view that helps define the system’s boundaries and prioritize key functionalities during development. In Figure 4.1, the primary actors include the parent, the child, the smartwatch, and the cloud system. A connection is established once the child wears the device, allowing it to continuously collect physiological data such as heart rate, body temperature and motion through integrated sensors.

The device processes the collected data to classify the child’s emotional state and presents this information to both the child and the parent via the smartwatch and mobile application, respectively. Simultaneously, the cloud system receives the data for secure storage and further analysis, generating comprehensive reports that can be accessed remotely. The diagram also highlights “include” relationships, which indicate optional sub-features integrated into certain processes, illustrating how specific functionalities support or extend the core use cases.

By capturing interactions between the actors and the system, this diagram provides a clear understanding of user-system dynamics and facilitates planning for development, testing, and deployment, ensuring that critical features are identified and implemented in an organized manner.

Figure 4.1 Use case Diagram

4.3.2 Sequence Diagram

A sequence diagram illustrates how objects interact over time to process a use case. The main components illustrated in Figure 4.2 include the main components, parent, child, the smartwatch, mobile application and cloud system. This figure highlights how data flows across the system in real time.

User interaction begins when the child wears the watch. The device continuously monitors biometric data such as the heart rate and body temperature if the device is worn. Regularly, the watch sends the data to the mobile application via the GPRS. The cloud stores the data and securely stores the information to run analytics (e.g., detecting abnormal heart rate). The watch also features an emergency alert button for the child to request immediate assistance, and the parent is immediately alerted with a vibration or push notification from the mobile application.

Additionally, the parent, if needed can view the current location of the child through the inbuilt GPS module. This is crucial in the event of elopement or truancy. In critical cases, the parent can also view reports if necessary for medical follow-up or assessments.

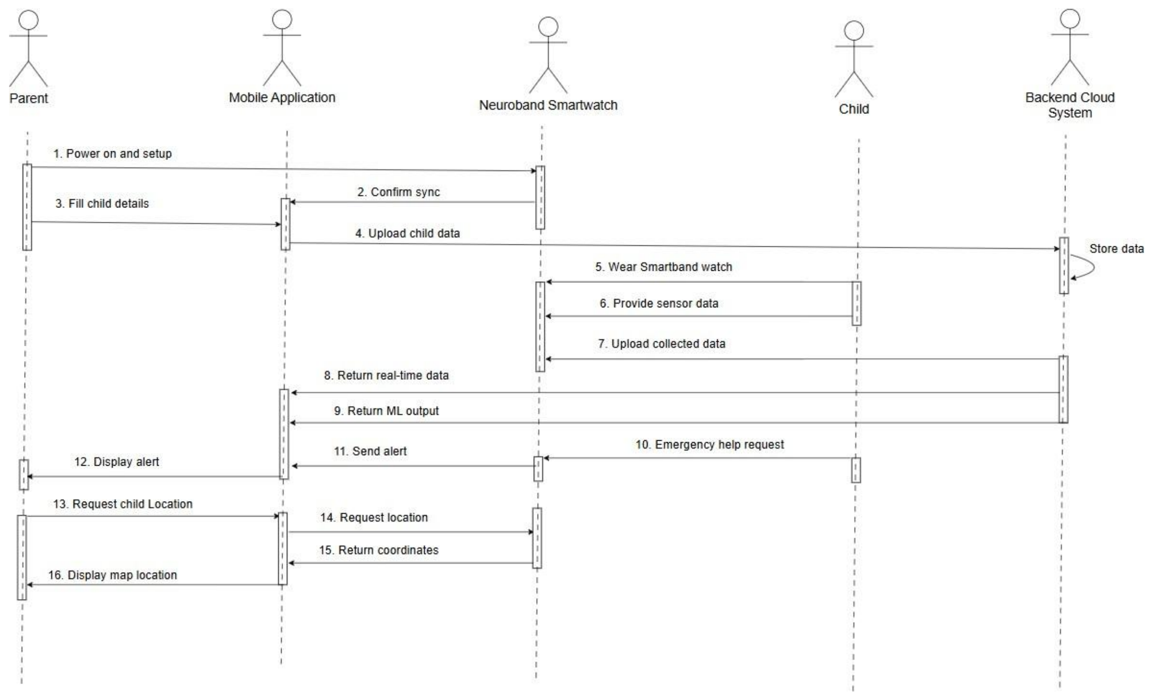

Figure 4.2 Sequence Diagram

4.3.3 Class Diagram

The class diagram illustrates the relationship between the entities in the system, and how they interact to handle data. The child is directly associated with the smartwatch in a one-to-one relationship, representing ownership and usage. The smartwatch aggregates the class of sensors, to detect heart rate, temperature and GPS location, through a one-to-many relationship. The individual sensor classes inherit from the main sensor class to provide the collected data since they cannot exist independently of the device. Data collected is then forwarded to the ML insight class, which contains methods for anomaly detection and generating health insights. The alerts are then generated from the alert class, which manages objects containing message type, timestamp and the message itself. The parent class is associated with both child and alerts, reflecting reception of the notifications and guardianship. This diagram emphasizes data encapsulation, cohesion among the hardware components and analytical role of machine learning in the system.

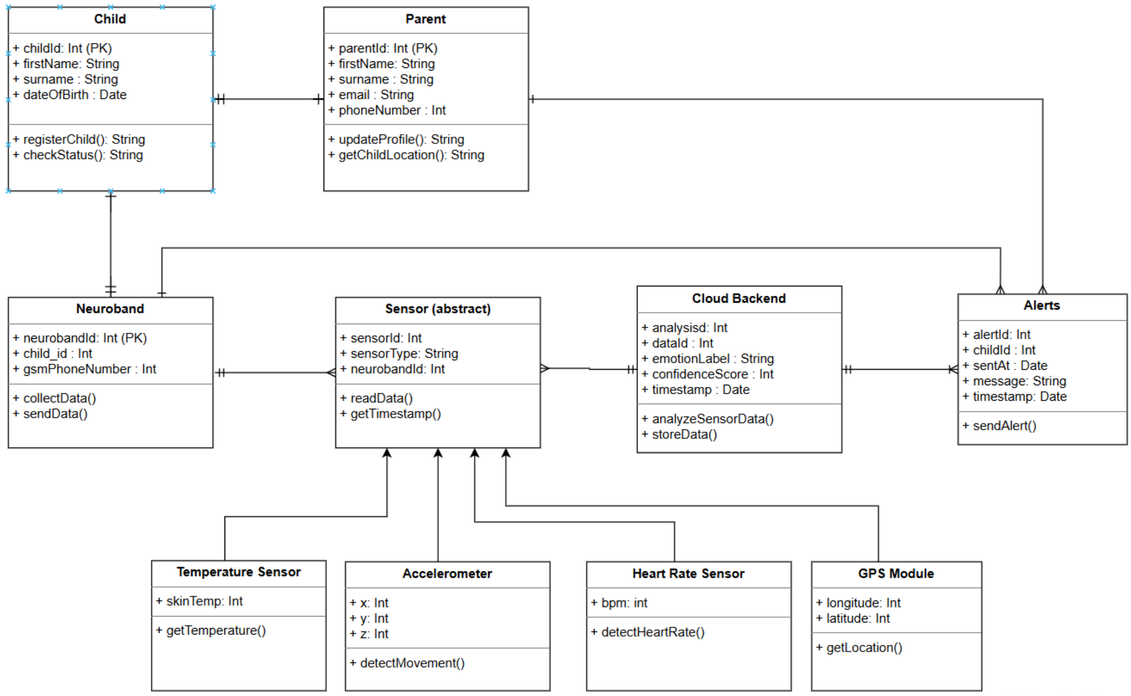

Figure 4.3 Class Diagram

4.4 System Design

4.4.1 Wireframes

To bring the Neuroband concept closer to reality, wireframes were created as a visual guide for the system's design and user interaction as shown in Figure 4.4. These wireframes were outlined to represent the structure and layout of key screens, including the onboarding pages, sign-in, and edit profile page. The goal was to illustrate how users would navigate through the app and access core features such as health monitoring, data visualization, and alerts. By focusing on functionality and flow, the wireframes were used as a blueprint that ensured the user experience remained intuitive and seamless before moving into implementation. The colours were selected to ensure a clear and appealing contrast throughout the application, making the interface both accessible and visually engaging. They were applied to guide the user's attention to critical information and highlight key features across the application, ensuring a smooth user experience.

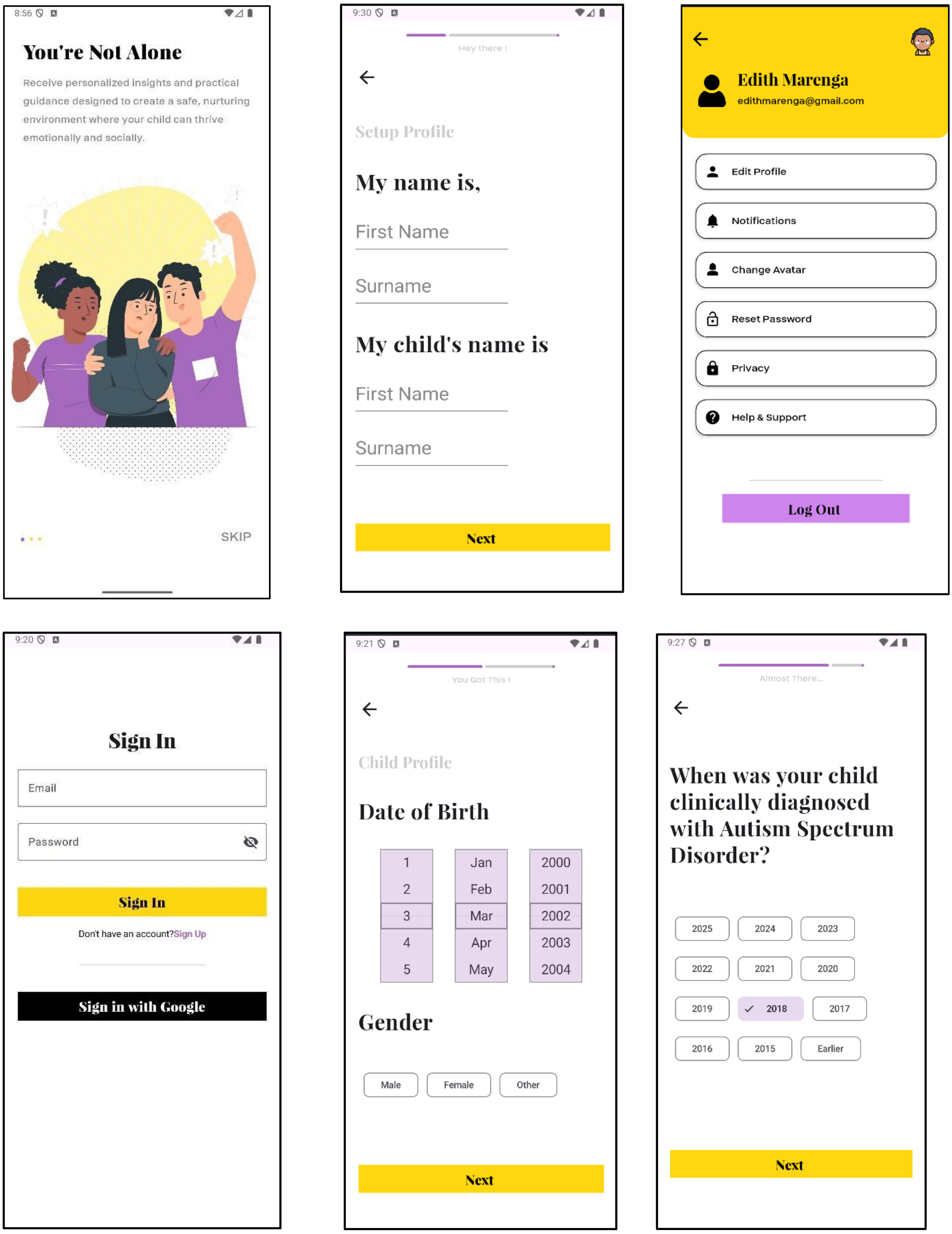

Figure 4.4 Wireframes

4.4.2 Entity Relationship Diagram

The Entity-Relationship Diagram (ERD) was created to represent the data structure and relationships within the Neuroband system. All entities, including users, sensors, health readings, and alerts, were identified and their attributes were defined to ensure accurate data representation. The parent entity has a one-to-one relationship with the child entity, therefore the Neuroband prototype is registered to only one child that provides the sensor data. For multiple child entities, their Neuroband smartwatches will refer to one cloud backend system to get the machine learning insights. Primary and foreign keys were assigned to enforce data integrity, and constraints were applied to prevent inconsistencies. The ERD was used as a blueprint for database design, ensuring that data storage and retrieval processes were structured, efficient, and aligned with the application's functional requirements.

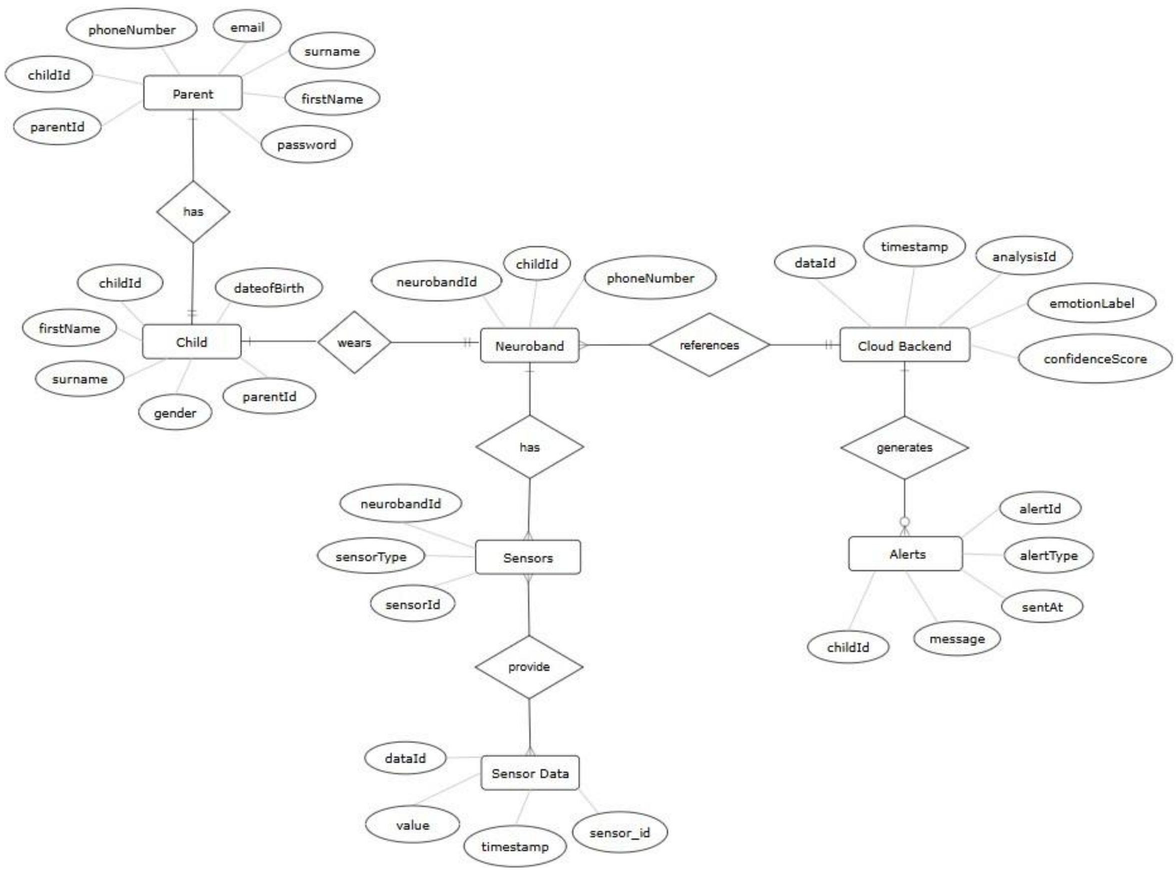

Figure 4.5 Entity Relation Diagram

4.4.3 Database Schema

The database of this system has been designed to include parents, children, the wearable Neuroband, sensors, cloud-based analysis and alerts, this is shown in Figure 4.6. Information regarding each parent has been stored in the parents table including basic personal information like name and contact details. Each parent has been linked to one or more children through the child's unique identifier. Personal details of the child, such as the name, gender and age have also been recorded in the children table. The smartwatch has been represented as the Neurobands table. Each Neuroband has been assigned only to one child and can be identified by a unique number or phone number. This device is installed with multiple sensors that are tracked in the sensors table and linked to the respective Neuroband smartwatch. All data collected by the sensors have been stored in the sensor_data table, these readings have been used as raw data for further analysis. Processed results and cloud-based analysis have been captured in the cloud_backend table. Each entry corresponds to a sensor data record, time of analysis and the emotion label generated by the machine learning model. Notifications are triggered based on the emotion label returned, and include a timestamp, descriptive message and type of alert. These are the stored in the alerts table.

Overall, the relationships between the entities have been established, ensuring a complete comprehensive system for monitoring and supporting children's wellbeing through connected devices and real-time analysis.

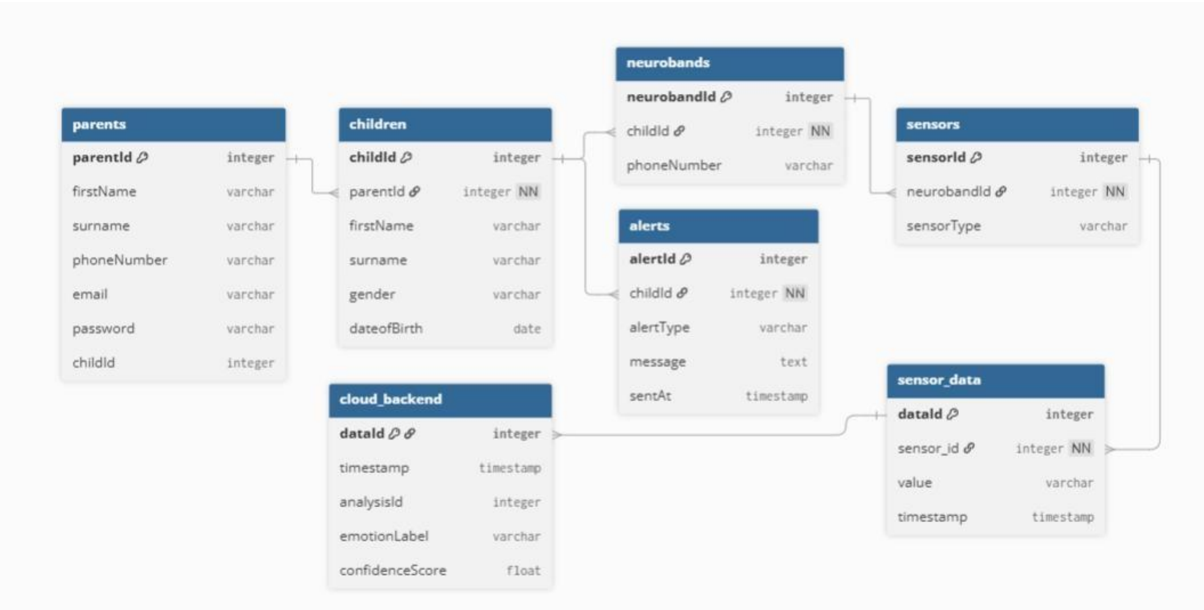

Figure 4.6 Database Schema

Chapter 5: System Implementation and Testing

5.1 Introduction

In this chapter, the implementation environment, dataset used and system testing procedures are described. Each section has been structured to provide a clear understanding of how the solution was developed and evaluated. This chapter includes details to ensure that environmental setup, data preparation and implementation were coherently performed during the development process of the Neuroband system. A brief description of the hardware and software requirements are also provided to support future similar works.

5.2 Description of Implementation Environment

The implementation environment was described in terms of how the product had been made available for use and the role of the hardware in the system. It was deployed on the ESP32 microcontroller, which served as the central processing unit, while the sensors such as the MAX3012, DS18B20, MPU6050 and NEO-6M GPS module were used to present real-time readings, and the SIM800L module to enable remote communication. This data was collected and rendered on a real-time database, InfluxDB. Arduino IDE had been utilized for coding and testing the prototype, while libraries specific to each sensor were employed to facilitate data processing. The system had been designed to be compatible with mobile devices for receiving alerts and updates, ensuring that the Neuroband could be practically accessible by end users.

5.2.1 Hardware Specifications

Item Name	Item Image	Description and Justification
D1 ESP32 2-in-1 dual-core CPU		Used as the main controller of the system, handling sensor data collection, processing, and communication.
NEO-6M GPS module		Used to provide real-time location tracking, useful for monitoring the wearer's movement or location in case of emergencies.

DS18B20 (Digital Temperature Sensor)		Used to measure body temperature to monitor health status and detect abnormal changes.
MPU 6050 (Accelerometer and Gyroscope)		Used to track motion, orientation, and activity levels, helping detect falls or stress related movement patterns.
0.96 Inch OLED Display module (128x64)		Used to display classified emotion directly on the band for quick access.
SIM 800L GPRS GSM Breakout Module		Used to enable communication over mobile networks, allowing the device to send alerts or data to caregivers or cloud servers.
Max 30102 Heartbeat Sensor Module		Monitors heart rate and blood oxygen levels, providing critical health metrics for real-time analysis of the child’s emotions.

5.2.2 Software Specifications

Software	**Version**	**Description**
Arduino IDE	2.3.6	Used to write, compile, and upload the source code to the ESP32 microcontroller, providing an easy-to-use platform for development and debugging.
Wire.h	2.3.8	Used to establish I²C communication between the ESP32 and various sensors,

		enabling efficient data transfer with modules such as the OLED, MPU6050, and MAX30102.
Adafruit_GFX.h and Adafruit_SSD1306.h	2.5.15	Used to control the 0.96" OLED display, allowing sensor readings and graphical elements to be rendered in real time.
TinyGPS++	0.0.4	Used to parse and interpret GPS signals from the NEO-6M module, providing accurate location data including latitude, longitude, and timestamp.
Google Maps SDK	18.1.0	Used within the Android application to visualize the GPS data on interactive maps, supporting features such as real-time location tracking and route display.
Kotlin	2.0.21	Used as the primary programming language for developing the Android companion application, offering concise syntax, strong safety features, and compatibility with modern Android development tools.
Google Colab	3.12.11	Used as a cloud-based platform for analyzing datasets and experimenting with machine learning models, providing access to Python libraries such as NumPy, Pandas, and Scikit-learn for data preprocessing and evaluation.
Firebase	32.3.1	Used to provide cloud-based storage and synchronization of sensor data, enabling seamless real-time communication between the Neuroband device and the mobile application.

5.3 Dataset Description

5.3.1 Training, Testing and Validation of the Dataset

The WESAD (Wearable Stress and Affect Detection) dataset was adopted as the primary source of data for this project. The dataset contains multimodal physiological signals such as respiration, body temperature, accelerometer readings and electrodermal activity from 15 participants under controlled conditions of baseline, stress and amusement. The dataset includes data collected from two devices, a chest device (RespiBAN) and a wrist device (Empatica E4). For this project, the wrist device features were used, which include the blood volume pulse derived from heart rate, skin temperature and the 3-axis accelerometer, this is shown in Figure 5.1.

```
# EDA already at target length
eda   = wrist_signal["EDA"].flatten()

# Build aligned DataFrame
wrist_df = pd.DataFrame({
    "ACC_x": acc_x,
    "ACC_y": acc_y,
    "ACC_z": acc_z,
    "BVP": bvp,
    "EDA": eda,
    "TEMP": temp,
})

print(wrist_df.head())
```

```
       ACC_x      ACC_y       ACC_z        BVP       EDA   TEMP
0 -23.000000  31.000000  127.000000  -8.270000  0.277864  31.97
1 -38.000000 -29.000315   39.995268 -12.626303  0.266351  31.97
2 -35.022712 -51.993691    1.971610  13.060500  0.195992  31.97
3 -29.997161 -31.009463   34.993376   1.869371  0.226694  31.95
4 -45.005047 -44.994953   12.997476  40.950526  0.126912  31.95
```

Figure 5.1 Features of the WESAD dataset

These signals were then segmented into fixed-length windows to transform the raw time series into structures suitable for machine learning. This ensures that continuous signals of the real-time data are converted into manageable chunks to extract meaningful features. This segmentation provides three windows, one for temperature, accelerometer and heart rate as shown in Figure 5.2.

```python
window_size = 256  # e.g., 10s if wrist is 64Hz
step_size = window_size // 2    # 50% overlap

def segment_signal(signal, window_size, step_size):
    segments = []
    for start in range(0, len(signal) - window_size + 1, step_size):
        segments.append(signal[start:start+window_size])
    return np.array(segments)

temp_windows = segment_signal(temp_signal, window_size, step_size)
acc_windows = segment_signal(acc_signal, window_size, step_size)
hr_windows = segment_signal(hr_signal, window_size, step_size)
```

Figure 5.2 Windows Derived from the Signals

For temperature, statistical measures such as mean and standard deviation were derived to represent short-term fluctuations. Accelerometer windows had been analyzed with motion-related characteristics including signal magnitude and variability. These features represent physical activity or movement patterns that may correlate with stress or relaxation. Heart rate windows have been examined for cardiovascular indicators such as average rate, variability and peak-to-peak intervals. These capture short-term cardiovascular responses that are highly relevant for stress detection. These features transform raw sensor data into compact and informative representations that form the process of model training and evaluation. The extracted features from each window are shown in Figure 5.3.

```python
def extract_temp_features(temp_window):
    return [
        float(np.mean(temp_window)),
        float(np.std(temp_window)),
        float(np.min(temp_window)),
        float(np.max(temp_window)),
        float(np.polyfit(range(len(temp_window)), temp_window, 1)[0])
    ]

def extract_acc_features(acc_window):
    x, y, z = acc_window[:,0], acc_window[:,1], acc_window[:,2]
    acc_mag = np.sqrt(x**2 + y**2 + z**2)
    return [
        float(np.mean(acc_mag)),
        float(np.std(acc_mag)),
        float(np.min(acc_mag)),
        float(np.max(acc_mag)),
        float(np.sum(acc_mag**2)/len(acc_mag))
    ]

def extract_hr_features(bvp_window, sampling_rate=64):
    from scipy.signal import find_peaks
    peaks, _ = find_peaks(bvp_window, distance=1)
    if len(peaks) < 2:
        rr_intervals = np.array([0.5])
    else:
        rr_intervals = np.diff(peaks) / sampling_rate
    hr_signal = 60 / rr_intervals if len(rr_intervals) > 0 else np.array([60])

    return [
        float(np.mean(hr_signal)),
        float(np.std(hr_signal)),
        float(np.min(hr_signal)),
        float(np.max(hr_signal)),
        float(np.percentile(hr_signal, 25)),
        float(np.percentile(hr_signal, 75))
    ]
```

Figure 5.3 Extracted Features for Each Signal

Once the physiological signals had been segmented and features extracted, the resulting data was organized into one feature matrix. Each row represented a single window of sensor readings summarized by the characteristics of the temperature, accelerometer and heart rate signals as show in Figure 5.4 .

```python
import numpy as np

def extract_features_from_window(acc_win, bvp_win, temp_win):
    """Extract scalar features from one window of signals."""
    # Compute HRV as diff of BVP
    hrv_win = np.diff(bvp_win)

    features = [
        # BVP
        np.mean(bvp_win), np.std(bvp_win),
        # ACC (x,y,z)
        np.mean(acc_win[:,0]), np.mean(acc_win[:,1]), np.mean(acc_win[:,2]),
        np.std(acc_win[:,0]), np.std(acc_win[:,1]), np.std(acc_win[:,2]),
        # TEMP
        np.mean(temp_win), np.std(temp_win),
        # HRV
        np.mean(hrv_win), np.std(hrv_win)
    ]
    return np.array(features)
```

Figure 5.4 Resulting Feature Array

Labels were then assigned to correspond to each feature of the window, as shown in Figure *5.5*. These labels were obtained from the WESAD dataset, which provides the annotated emotional states based on the control experiment, baseline – 0, stress – 1 and amusement – 2. With respect to Neuroband, when a child transitions from being calm to suddenly crying, the windows overlap to capture both states in one session. To avoid confusion, the label for that window will be assigned based on the most frequent state observed. Therefore, if the child crying formed 60% of that segment, the window was labeled as 1 (stress).

```python
# ----------------------------
# Align labels per window
# ----------------------------
y = []
for start in range(0, len(labels) - window_size + 1, step_size):
    # Most frequent label in the window
    y.append(np.bincount(labels[start:start+window_size]).argmax())



# Find the minimum number of windows
n_windows = min(len(hr_windows), len(temp_windows), len(acc_windows))

# Truncate to match number of windows
y = np.array(y[:n_windows])
```

Figure 5.5 Assign Labels to Windows

After extracting features from each sensor window, the features were combined into a single feature matrix, denoted as X. In this matrix, each row corresponds to one time window of sensor data, and each column represents a feature extracted from either of the signals. The corresponding labels for each window were stored in vector y, where each element of y represents the condition associated with the row of X, this is illustrated in Figure 5.6.

```
# Truncate all windows to the same number
hr_windows = hr_windows[:n_windows]
temp_windows = temp_windows[:n_windows]
acc_windows = acc_windows[:n_windows]

# Now extract features
temp_features = np.array([extract_temp_features(w) for w in temp_windows])
acc_features = np.array([extract_acc_features(w) for w in acc_windows])
hr_features = np.array([extract_hr_features(w) for w in hr_windows])

# Combine features
X = np.hstack([hr_features, temp_features, acc_features])

# Align labels per window
y = y[:n_windows]  # truncate labels as well
```

Figure 5.6 Final Feature Matrix

In summary, this section describes how the raw sensor data was processed to prepare it for the machine learning model. Features were extracted from heart rate, temperature and accelerometer signals for each time window, and combined into a single input matrix. This structured dataset provides a clear and organized foundation for training and evaluating the predictive model in later sections.

5.4 System Implementation

5.4.1 Model Training and Evaluation

Once the statistical and frequency features were derived, and combined into the input matrix, the dataset was split into two, a training set and testing set. In this project, 80% of the data was allocated to training while 20% was reserved for testing, as shown in Figure 5.7. This is important because it prevents the model from memorizing the dataset and instead forces it to learn the general patterns that distinguish different emotional states. By doing this, we simulate practical conditions where the model must make predictions on data it has never encountered before, ensuring unbiased evaluation.

```python
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score


X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.3, random_state=42, stratify=y
)
```

Figure 5.7 Splitting the Dataset

The training stage involves fitting the Random Forest Classifier (RFC) to training the data. This is an ensemble learning method that combines the predictions of multiple decision trees to improve accuracy and reduce overfitting. Individual decision trees are prone to memorizing noise in training data, while a Random Forest builds many trees using different subsets of data and features. It then aggregates their predictions through majority voting leading to a more stable model, better at capturing complex relationships in data (Salman et al., 2024). Training the Random Forest consisted of passing the features and labels into the model where multiple trees were constructed. The choice of Random Forest was guided by its ability to store a decision forest for future reference which proves helpful where input data fluctuates instantaneously (Achmad Ridwan et al., 2024).

```python
# --- Train/test split ---
X_train, X_test, y_train, y_test = train_test_split(
    X_clean, y, test_size=0.3, random_state=42, stratify=y
)

# --- Train Random Forest ---
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)

# --- Predictions ---
y_pred = rf_model.predict(X_test)

# --- Save the trained model ---
filename = "neuroband_rf.pkl"
with open(filename, "wb") as f:
    pickle.dump(rf_model, f)
```

Figure 5.8 Final Model Generation

5.4.2 Evaluation Metrics

The trained model achieved an overall accuracy of 91%, which means that out of all predictions made, approximately 9 out of every 100 instances were incorrect. It is often calculated as the sum of accurate predictions (TP+TN) divided by the total number of data sets (P+N), (Vujovic, 2021). Accuracy is a good general indicator, but since the dataset contains multiple classes (baseline, amusement and stress), other metrics were included to evaluate model performance. In the Figure 5.9, the level of precision, recall and F1-score were computed and displayed.

Precision is a key performance evaluation metric used to evaluate how accurately a model identifies positive cases. It is also referred to as the positive predictive value and is mathematically calculated as the number of correct positive predictions (TP) divided by the total positive predictions, both false and true (TP+FP) (Vujovic, 2021). For this model, the precision of 93% would indicate that if the emotion detected is stress, the model will be correct 93% of the time. Higher precision is particularly valuable in stress detection because it reduces the risk of misclassifying normal states as stress, which would lead to unnecessary interventions and false alarms.

```python
# --- Evaluation ---
print("Random Forest Performance:")
print("Accuracy:", accuracy_score(y_test, y_pred))
print("Precision:", precision_score(y_test, y_pred, average='weighted'))
print("Recall:", recall_score(y_test, y_pred, average='weighted'))
print("F1 Score:", f1_score(y_test, y_pred, average='weighted'))
print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

```
Random Forest Performance:
Accuracy: 0.9166666666666666
Precision: 0.9333333333333332
Recall: 0.9166666666666666
F1 Score: 0.9074074074074074
```

Figure 5.9 Accuracy, Precision and F1-Score of the Model

The recall, also referred to as sensitivity, is a measure of the actual positives the model classifies. It is calculated as the number of true positives (TP) divided by the sum of true positives (TP) and false negatives (FN), (Vujovic, 2021). This Neuroband model derived a recall of 91.7% therefore, out of all samples that should have been classified as positive, it correctly classified roughly 92% of them. The F1-score is a measure of the harmonic mean between precision and recall, which primarily reflects the type of error, either false positives or negatives, that the model makes (Cabot & Ross, 2023). A score of 91% suggests that the model performs consistently in both precision and recall, ensuring that it avoids a large number of false positives. A high F1-score often indicates a well-balanced model that performs reliably across detection and accuracy of predictions (Naidu et al., 2023).

Confusion matrices illustrate absolute truths as rows and predicted classifications as columns as shown in Figure 5.10. They delineate the number of true positives, false positives (type-I error), true negatives and false negatives (type-II error), which are used to derive recall, precision and accuracy (Cabot & Ross, 2023). It provides a more detailed view of how the model performs across individual classes. This matrix also helps identify whether the model is biased towards one class.

As shown in Figure 5.10., class 0 represents baseline/neutral, class 1 represents stress and class 2 shows amusement. Class 0 shows that 6130 samples were correctly predicted as class 0, which are true positives (TP), and 27 samples were incorrectly predicted as class 1, and lastly 34 as class 2. This indicates that the model performs well for class 0, with few misclassifications. The middle row, class 1, shows that 3501 samples were correctly identified (TP), 75 samples were misclassified as class 1, with even less, 13 misclassified as class 2. Although most predictions were correct, some samples from class 1 were classified as class 0, possibly due to similar physiological signal patterns between the states. The bottom row shows that 1841 samples were correctly predicted as class 2, with 74 incorrectly classified as class 0, and 40 as class 1. While performing well, it shows slightly weaker performance from class 1 and 0, this is attributed to the WESAD dataset containing comparatively fewer training samples to equally recognize the amusement state.

```python
# --- Confusion Matrix ---
cm_rf = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(6, 5))
sns.heatmap(cm_rf, annot=True, fmt="d", cmap="Blues")
plt.title("Random Forest Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("True")
plt.show()
```

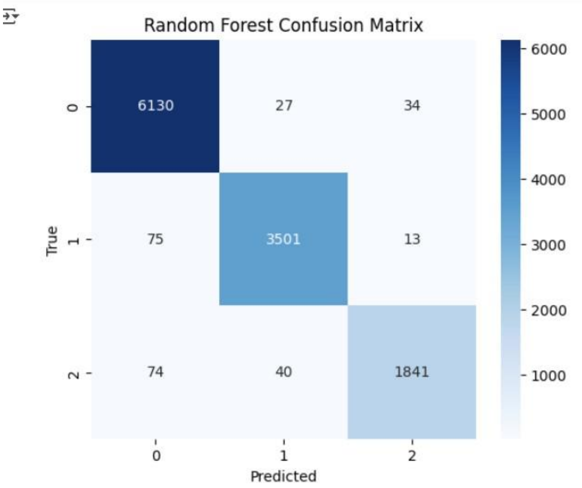

Figure 5.10 Confusion Matrix of the Model

From the confusion matrix, it is evident that the baseline emotion (class 0), dominates the model, with the it correctly classifying majority of the baseline samples (6130). This dominance is perceived as beneficial because it shows the model has effectively learned the characteristics of the normal physiological state, which serves as the reference point for distinguishing between stress and amusement. For the children with autism, this classification ensures that when rapid deviations occur, such as increased heart rate and movement associated with stress, the model can detect them more reliably.

Overall, these results imply that the model is intentionally calibrated, efficient, and dependable. It demonstrates that the learning algorithm has effectively captured the underlying patterns in the data, allowing it to generalize well to unseen samples. Such performance levels indicate that the model could be confidently used for real-world applications, particularly in detecting physiological or emotional states from wearable sensor data. The balance between recall and F1-score highlights that the model is not biased toward over-predicting one class and maintains robust performance across different evaluation criteria, making it a strong candidate for deployment or further refinement.

5.5 System Implementation

5.5.1 Sensor Layer

This section outlines the various components that form the foundation of the Neuroband system. These modules were responsible for data collection and physiological signal acquisition before being transmitted to the cloud database.

i. MAX30102 Pulse Oximeter and Heart Rate Sensor

The MAX30102 is an integrated pulse oximetry and heart rate monitor sensor module that combines two LEDs (Red and Infrared), a photo detector and low-noise analog signal processing. The device operates via the I2C communication protocol and can measure the light absorption variations caused by blood volume changes in the microvascular bed of tissue. In this project, the Infrared signal (IR) from the MAX30102 was used to calculate the blood volume pulse (BVP) signal, which is directly proportional to the changes in blood flow. This has been done to align the sensor data with the parameter BVP, present in the dataset used to train the Neuroband model. From this signal, the heart rate was derived for better user perception and understanding of the MAX301012 readings.

The BVP signal is obtained from the raw infrared (IR) light intensity readings. The raw signal is first filtered to remove noise and baseline drift using a bandpass filter (typically between 0.5 – 4Hz) to capture heart rate variations corresponding to 30-240 beats per minute.

$$BVP(t) = \text{BandpassFilter}(\text{IR}(t))$$

Equation 5.1 BVP Filter Equation

After obtaining the filtered BVP signal, the heart rate was calculated by detecting the peaks in the waveform. Each peak corresponds to a heartbeat. The time interval between successive peaks (T_{RR}) is used to compute heart rate as:

$$HR = \frac{60}{T_{RR}}$$

Equation 5.2 Heart Rate Derivation

Where:

- T_{RR} is the average time (in seconds) between two consecutive peaks of the BVP signal,
- HR is the heart rate in beats per minute (BPM).

The MAX30102 provides high sensitivity in pulse detection, making it ideal for continuous physiological monitoring applications such as stress analysis, as used in the WESAD dataset. It has a sampling rate of 50 – 1000 samples per second and overall low power consumption, making it suitable for wearables. For this project, it was configured to provide one sample per second for testing purposes.

ii. DS18B20 Digital Temperature Sensor

The DS18B20 is a digital thermometer that provides 9-bit to 12-bit Celsius temperature measurements and communicates over a 1-Wire bus, meaning it only requires one data line and ground for communication. It was used in this project to measure skin temperature, an important physiological parameter associated with emotional states. The sensor outputs temperature directly from its internal analog to digital converter. It was also specifically chosen for this project for its digital precision, compact size and low hardware complexity.

The DS18B20 has a range of -55°C to +125°C and an accuracy of ±0.5°C per reading. According to (Diamond et al., 2021), typical human body temperatures range from 35.2°C to 37.4 °C and does not differ by age. For this project, the readings were limited to between 34.0°C (hypothermia) and 42.0°C (high fever), as shown in Figure 5.11. Hence, readings beyond this were determined as sensor noise or error due to loose wires and consequently ignored.

```
void loop() {
  sensors.requestTemperatures();

  delay(750);

  float tempC = sensors.getTempCByIndex(0);

  if (tempC == DEVICE_DISCONNECTED_C) {
    Serial.println("Sensor disconnected!");
  } else {

    // Check if the reading is within human body temperature range
    if (tempC >= 35.0 && bodyTemp <= 42.0){
      Serial.print("Body Temperature: ");
      Serial.println(tempC);
    }
    else {
      Serial.println("Invalid reading out of range: ");
    }
  }
  delay(1000);
}
```

Figure 5.11 DS18B20 Acceptable Range

iii. MPU6050 Accelerometer

The MPU6050 is an Inertial Measurement Unit (IMU) that contains an inbuilt 3-axis accelerometer and gyroscope. The accelerometer measures linear acceleration along the X, Y and Z axes, while the gyroscope measures angular velocity (rotation) around the X, Y and Z axes. The accelerometer was crucial to capturing motion data from the subject's wrist, representing hand movement or activity level which provides context to physiological changes. This data is crucial in identifying the emotional state of children with autism. In extreme agitation, tantrums often involve rapid hand movements in a repetitive and uncoordinated manner. The MPU6050 bridges the gap between behavioral expression and emotional inference, allowing the system to detect stress even when physiological indicators might be ambiguous.

To represent the overall motion intensity, assuming the accelerometer readings are denoted as Ax, Ay, Az, the magnitude of the acceleration vector is computed as:

$$A_{mag} = \sqrt{A_x^2 + A_y^2 + A_z^2}$$

Equation 5.3 Acceleration Magnitude Formula

Where:

- Ax is acceleration along the X axis
- Ay is the acceleration along the Y axis
- Az is the acceleration along the Z axis

This measure allows the system to differentiate between resting, moving and high-activity states.

iv. NEO-6M GPRS GSM Module

The NEO-6M is a GPS module that receives signals from multiple satellites to identify a device's exact geographic location. In this system, it is used to collect real-time location data such as longitude and latitude. This module requires a clear view of the sky to obtain the data and present it in a format known as NMEA (National Marine Electronics Association). This format contains sentences that contain details such as time, latitude, longitude, number of satellites and signal accuracy. Sentences typically begin with a dollar sign and have comma-separated values that describe specific information about the GPS readings.

5.5.2 Circuit Design and Schematic Diagram

The circuit integrates all the essential hardware components that enable the wearable system to capture physiological and motion data, process it and transmit it wirelessly to the cloud for analysis. The circuit was simulated using EasyEDA, to ensure the components are interconnected correctly. The main control unit is the ESP32 D1 microcontroller which provides computational capability for seamless communication with the other components on the prototype. The design follows a modular approach to simplify debugging and ensure scalability.

The MAX30102 pulse oximeter is connected to the ESP32 using the I²C communication protocol, with the SDA (data cable) linked to IO23 and SCL to the IO22. This module operates at 3.3V and captures the infrared signals (IR) and red LEDs which determine the heart rate and blood volume pulse (BVP). The DS18B20 digital temperature sensor is interfaced via the OneWire protocol on IO25. A resistor was included in the circuit to regulate the power supply to the sensor. The MPU6050 module is also connected through the I²C bus, allowing it to share the connection pins with the NEO-6M GPS sensor. An OLED display (128x64 pixels) is connected to the same I²C bus to provide real-time visual feedback during testing of the sensors. The Neo-6M GPS module provides real-time geolocation data that can be used to monitor the location of the child. It communicates with the ESP32 using the UART protocol, typically connected via TX to IO22 and RX to IO23.

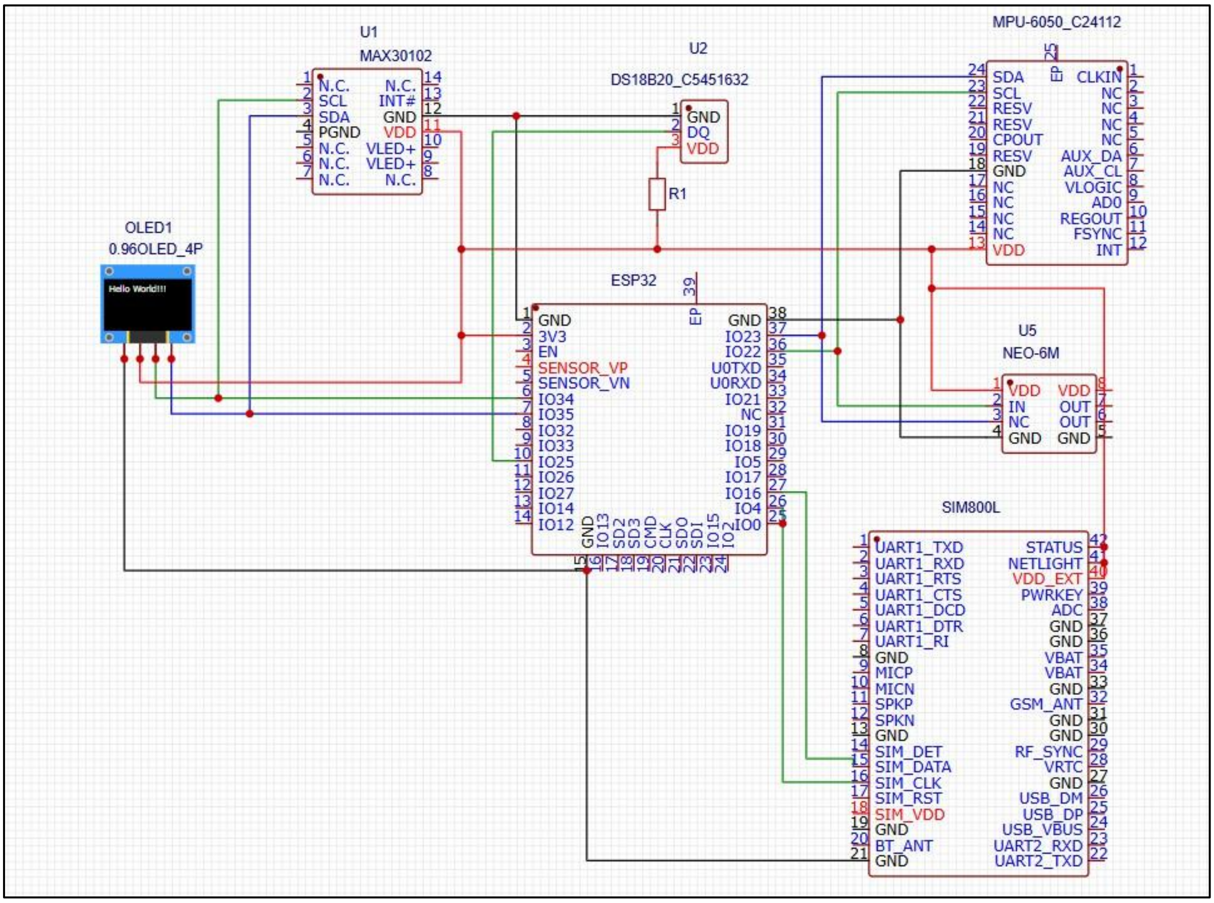

Figure 5.12 Prototype Schematic Diagram

5.5.3 Communication and Cloud Layer (SIM800L)

This layer of the Neuroband system is responsible for sending the data collected by sensors to the InfluxDB platform where it can be stored and analyzed. The system incorporates a GSM cellular network provided by the SIM800L module that is loaded with a SIM card, which must have an active data plan.

Once the sensors collect their readings, the data is processed by the ESP32 and sent over the GSM connection, enabling real-time transfer and remote monitoring of the physiological data. For secure handling of the data, InfluxDB Cloud is automatically configured with HTTPS communication to encrypt data during transmission. This guarantees that the server always uses SSL/TLS encryption which establishes a secure connection between the device or backend API. By using enabling HTTPS, InfluxDB ensures that all communication between the applications is encrypted. This protects sensitive physiological data from interception or unauthorized access during transmission, thereby maintaining data privacy and integrity.

5.5.4 Neuroband Mobile Application

The mobile application serves as the user interface for parents and caregivers. It allows viewing of the physiological data, reports and state of the child. It has been developed to provide a simple, responsive and user-friendly experience that can run on Android devices.

The application communicates with the backend through a RESTful API, enabling it to retrieve and display real-time data such as sensor readings or location updates. The data is retrieved from InfluxDB and parsed into JSON responses for compatibility before sending it to the mobile application. Thunder Client and Ngrok were incorporated in testing and verifying functionality of API endpoints to ensure HTTPS requests made from the mobile application were successful. To maintain data security, all communication between the mobile app and the server is encrypted using HTTPS. Sensitive information, such as user details, is stored securely in using encryption libraries. Additionally, authentication mechanisms ensured that only authorized users can access certain features.

5.6 System Testing

5.6.1 Authentication Testing

This testing focuses on verifying that the system correctly identifies and authorizes legitimate users, devices and data sources before granting access. It ensures that caregivers or parents can only access their own data and no one else's, therefore maintain the privacy and confidentiality of the data.

Table 5.1 Authentication Testing

Test Case	Description	Test Data	Expected Outcome	Actual Results	Test Verdict
TC001	Password validation on sign up	Email: testing@gmail.com Password: test123	Descriptive error message displayed, "Password must be at least 8 characters long, include uppercase letter,	As expected	Pass

			number and special character”		
TC002	Sign up	Email: testing@gmail.com Password: Tev39gl13t!!	Email Notification	As expected	Pass
TC003	Password validation on login	Email: testing@gmail.com Password: Tev3noe234!!	Descriptive error message displayed, “Password is incorrect”	As expected	Pass
TC004	Login Verification	Email: testing@gmail.com Password: Tev39gl13t!!	Email Notification with OTP	As expected	Pass
TC005	Session Management	parentId : 001 childId : 001	Child’s full name is displayed on dashboard when parent logs in. Logged-out sessions cannot access restricted endpoints.	As expected	Pass

5.6.2 Prototype Testing

i. MAX30102 Pulse Oximeter and Heart Sensor

The MAX30102 sensor was tested to ensure it accurately measures heart rate and blood oxygen (SpO_2) levels. The sensor was connected to the ESP32, and a test sketch uploaded on the Arduino IDE to verify its communication with the microcontroller. The serial monitor was then used to observe live readings of pulse rate and verify functionality. The sensor’s red and infrared LEDs illuminated and consistent changes in readings were noted when a finger was placed over the sensor, confirming proper wiring, this is illustrated in Figure 5.13. These results showed that the MAX30102 was functioning correctly, with reliable signal acquisition and ready for use in the final prototype.

Figure 5.13 MAX30102 Test Results

ii. MPU6050 Accelerometer

The MPU6050 sensor was tested to verify its functionality and accuracy in measuring acceleration and angular velocity. The test involved connecting the module to the ESP32 using the I2C interface, with the SDA and SCL pins properly configured. After uploading a test program as shown in Figure *5.14* , the sensor returned real-time data that were observed on the serial monitor, displaying values along the X, Y and Z axes. Consistent readings that changed according to the sensor's movement confirmed that both the accelerometer and gyroscope were functioning correctly. This showed that the MPU6050 was properly wired, calibrated and ready for integration into the main system for motion sensing and orientation detection.

The readings in Figure *5.14* represent the magnitude and direction of movement tested. Negative readings signify motion or tilt in the left direction, while positive readings indicate movement to the right the same axis. For the Y axis, positive values represent forward movement, while negative values represent backward movement. The Z axis returns positive values for upward motion and negative for downward motion.

Figure 5.14 MPU6050 Test Results

iii. DS18B20 Digital Temperature Sensor

The DS18B20 sensor was tested once it was setup using the 4.7kΩ pull-up resistor between the data line and the power line. This ensured a stable supply of power that guaranteed its functionality and didn't damage the component. The test procedure involved initializing communication with the 1-Wire protocol and generating a loop to read the temperature data every second. As seen in Figure *5.15*, the values changed approximately when the sensor was exposed to warm and cool environments, confirming that the sensor was functioning correctly.

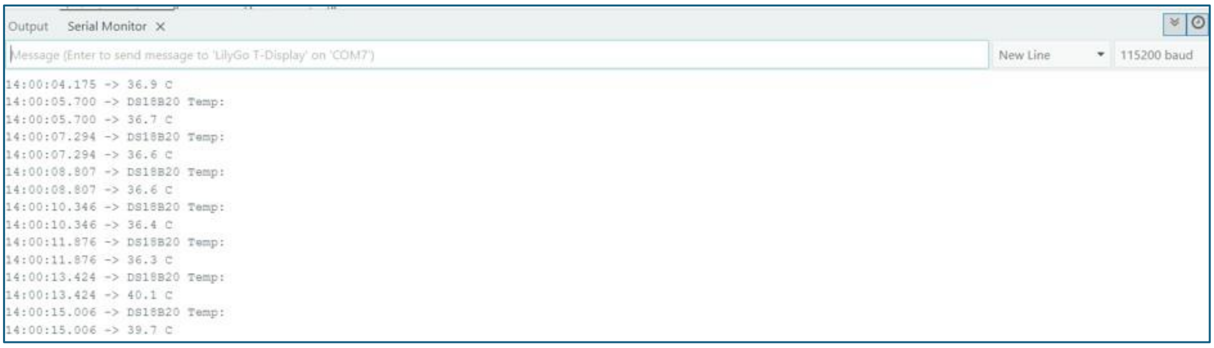

Figure 5.15 DS18B20 Test Readings

iv. SIM800L GPRS GSM Module

To verify that the SIM800L module could send and receive text messages and send data over the cellular network, a series of AT commands were executed through the serial monitor of the Arduino IDE. Table 5.2 shows the list of commands used to test SIM800L GSM functionality and their relevance to the testing process, from SIM detection, sufficient network signal and registration to a network.

Table 5.2 SIM800L GSM Test Commands

Command	**Expected Response**	**Relevance**
AT	OK	Confirms successful communication between ESP32 D1 and SIM800L.
AT+CPIN?	+CPIN: READY	Confirms SIM card is detected and unlocked.
AT+CREG?	+CREG: 0,1	Indicates SIM registration to a network (Safaricom/Airtel/Telkom)

AT+CSQ	+CSQ: [15-20], 0	SIM signal quality, the higher the value in the range, the better the signal.
AT+CMGF=1	OK	Sets SMS mode to text format.
AT+CMGS="+254XXXXXX"	"Hello from ESP32 + SIM800L! "	Sends a test message to a phone number.,

Figure 5.16, shows the results after testing the SIM800L with the ESP32 microcontroller, it displays the responses of all the AT commands executed, confirming successful communication. Each command returned the expected response (such as OK, +CPIN: READY, +CREG:0,1 and valid signal strength values). The AT+CSQ command indicated a strong network connection and implies that the module had reliable access to the cellular network, ensuring stable communication for sending and receiving SMS messages or transmitting data. Additionally, this confirmed that the antenna and SIM card were functioning properly and that network conditions were stable for communication.

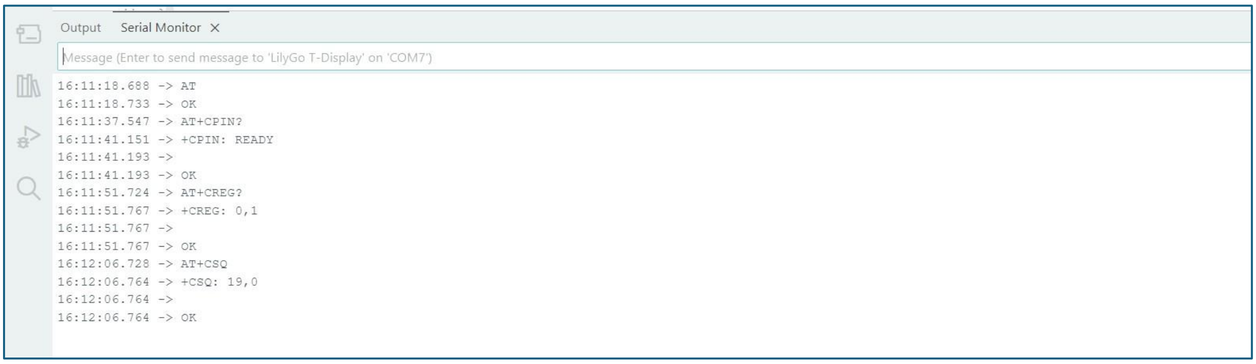

Figure 5.16 SIM800L Test Results

The AT+CMGS module was the SMS sending test carried out to confirm the SIM800L module could transmit text messages successfully. After setting the text mode using the command, the destination phone number was specified with a functioning phone number to send the message. The SMS was promptly transmitted and verified by checking the recipient's phone as shown in Figure 5.17 , confirming that the SIM 800L could reliably send SMS messages through the network.

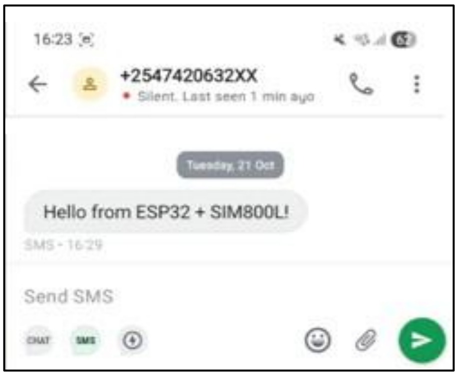

Figure 5.17 SIM800L SMS Test

v. NEO-6M GPS Module

Before integrating the GPS module, it was necessary to conduct a series of tests to ensure that the module could correctly acquire satellite signals and transmit accurate location data. The goal of this test was to verify the module's connectivity, signal acquisition and data output format. After approximately 30-60 seconds, once the module locked onto multiple satellites, the serial monitor displayed valid longitude and latitude readings, which were continuously updated as the module's position changed.

It was observed that the module acquired a valid GPS fix when in an open area with a clear view of the sky. Additionally, the transmitted coordinates were accurate, indicating successful communication of the module with the ESP32 and the satellites.

Figure 5.18 GPS Module Test Results

5.6.3 API Integration and Real-Time Data Flow Testing

This section represents the data flow and pipeline from the sensor layer to the cloud database, through the backend API and finally to the mobile application interface.

This first stage as shown in Figure 5.19 involves capturing raw sensor data from the prototype. The data returned includes IR values to derive heart rate, the acceleration data and the body temperature. This verifies that the device is actively sensing and transmitting data before it is sent to the cloud.

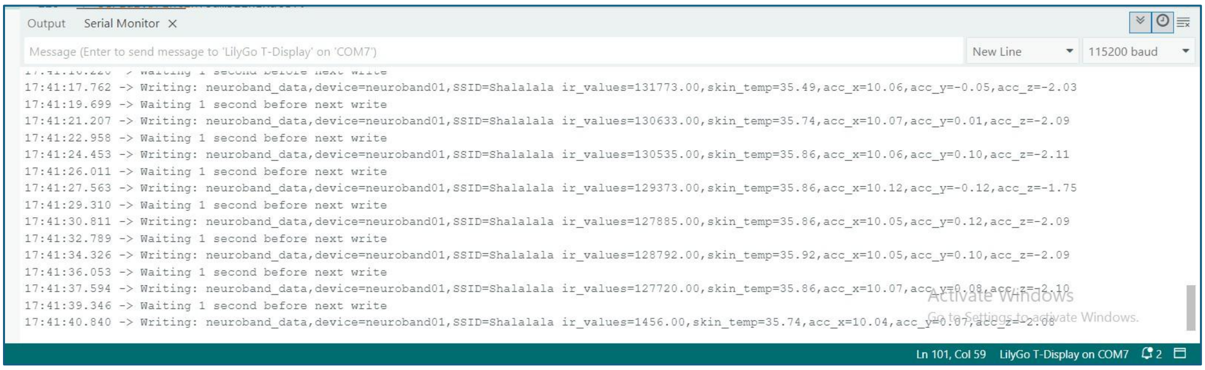

Figure 5.19 Data Collection from Sensors

The GSM module (SIM800L) connects the ESP23 to the internet via the cellular network. It uses HTTP POST requests to send sensor readings to the InfluxDB backend where the data is rendered on a dashboard as shown in Figure 5.20. This confirms that the cloud is receiving and storing real-time data, allowing for monitoring and historical analysis.

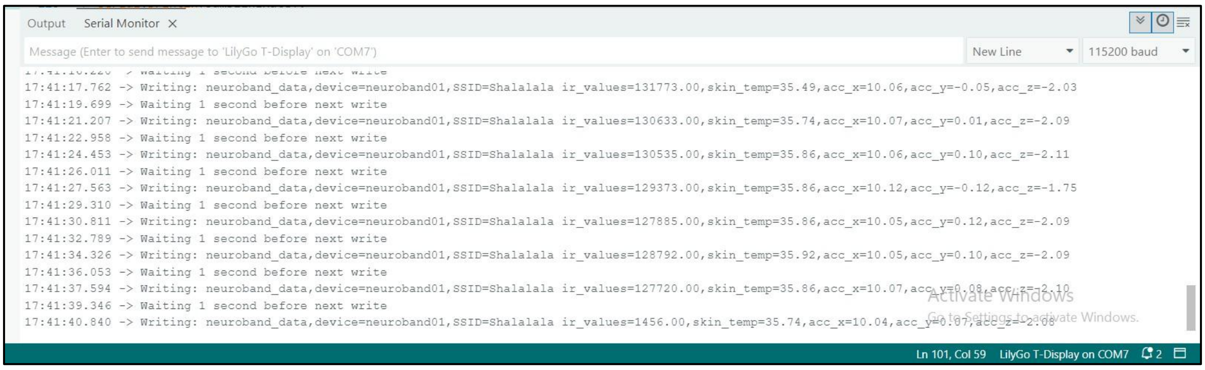

Figure 5.20 InfluxDB Dashboard Storing Data

The Flask backend acts as an intermediary between the prototype and the mobile application. It defines RESTful API endpoints such as /api/query, to return the values from InfluxDB. The data is the formatted as JSON and sent to the frontend. The Figure 5.21 shows the Flask terminal output showing successful GET requests being made once the user loads the page that displays this data. This demonstrates that the backend is correctly retrieving and streaming data to the frontend in real-time.

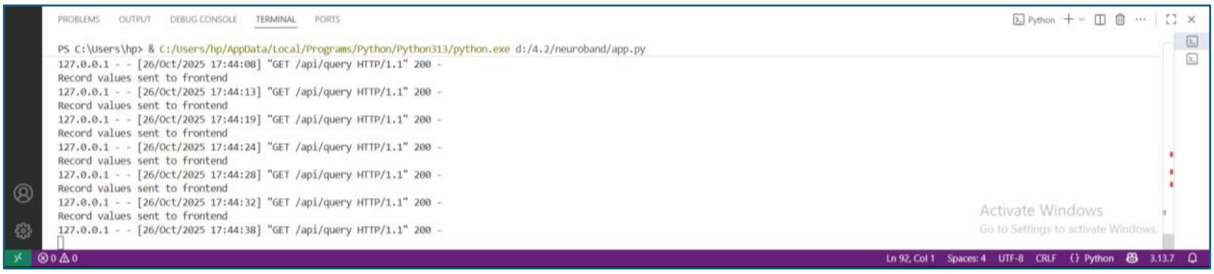

Figure 5.21 API Test Results

The final stage is the mobile app, where users can view their children's real-time physiological data in a user-friendly interface. The application continuously receives data over the API, updating graphs and metrics (heart rate, movement patterns). This is illustrated in Figure 5.22 with a simple column to show the readings received from the backed. This confirms that the app is successfully receiving and updating data through the entire pipeline.

Figure 5.22 Mobile Application API Testing

5.6.4 Model API Testing

To ensure reliability and performance of the Neuroband system, the model was tested to verify functionality of both the hardware and software components. The goal was to verify that there is clear communication between the collection of data from the sensors to the cloud and eventually into the model.

After successfully training and deploying the model as an API, testing was conducted using Thunder Client to verify that the model endpoint responds correctly and returns the appropriate emotion based on input data. This has been illustrated by Figure 5.23.The Flask endpoint was defined as POST http://127.0.0.1:5000/predict, with the sample request body (JSON) used to test the endpoint of the API. The status showed 200OK, indicating that the endpoint is accessible and working normally.

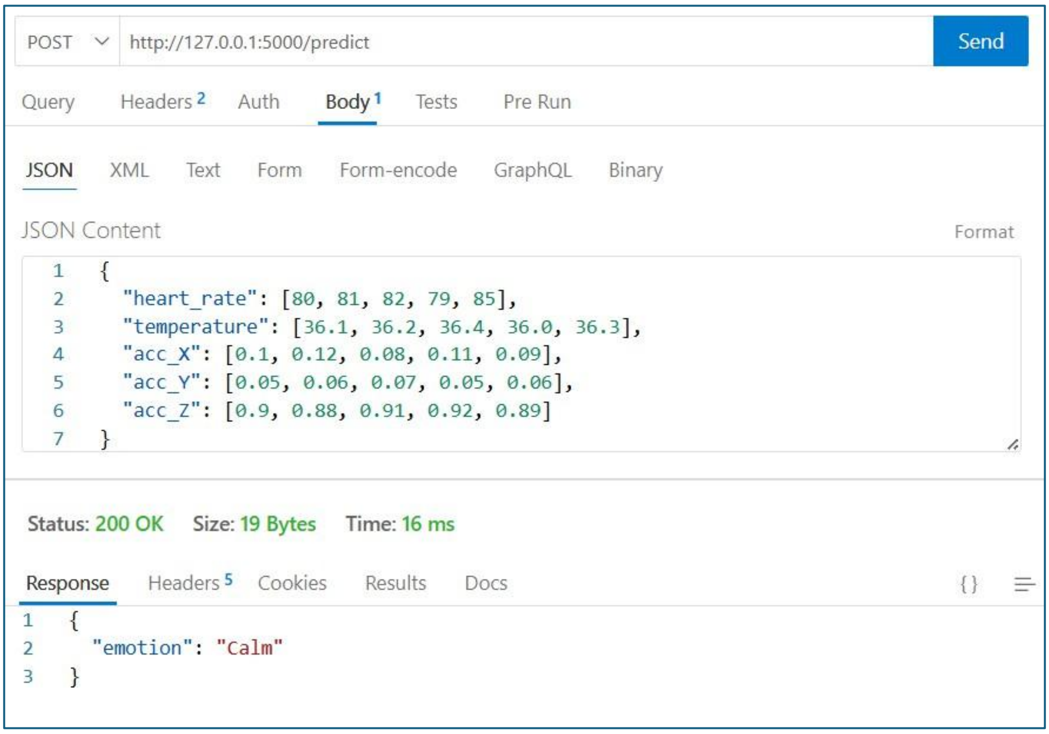

Figure 5.23 Model API Testing

The purpose of this test was to ensure that the model API is running and accessible to the frontend through its defined route /predict. It also ensures that input sensor data sent via POST requests is correctly received and processed, the API then returns the classified emotion in JSON format.

Additional invalid input tests were performed to ensure the API responded to null or incomplete data. When empty arrays are sent for one or more of the required parameters, the API detects the missing data and returns an informative error message, as shown in Figure 5.24 .This helps confirm that the trained model will not attempt to process empty or corrupted sensor readings which could otherwise produce unreliable emotion predictions.

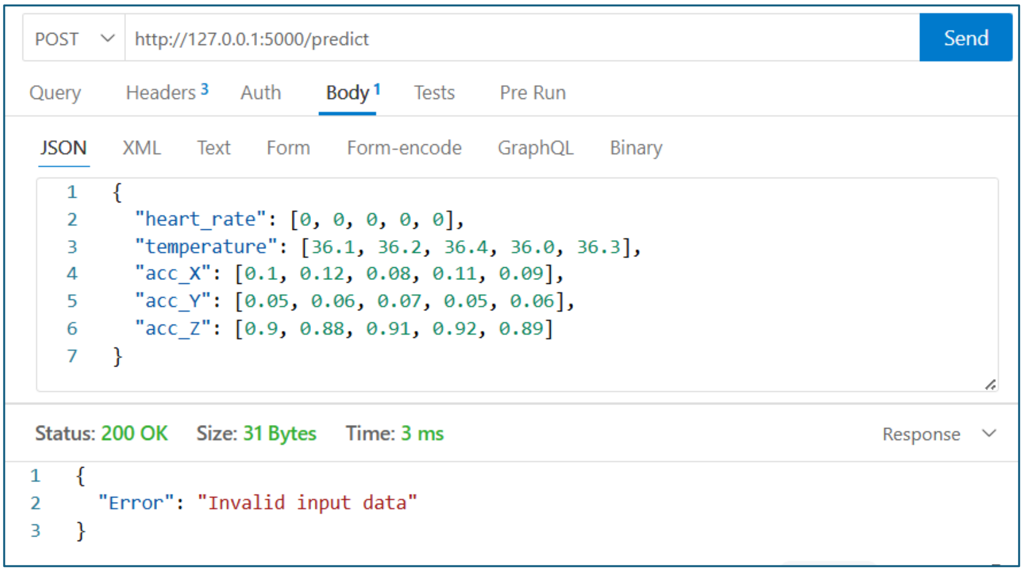

Figure 5.24 Model Invalid Input Testing

Chapter 6: Conclusion, Recommendation and Future Works

6.1 Conclusion

This project demonstrated the integration of hardware and software components to achieve real-time physiological data monitoring. The system leveraged the power of IoT, cloud computing, machine learning and mobile technology to create an intelligent and responsive wearable that can help parents and caregivers better understand a child's emotional and physical state.

The system's design not only allows focus on technical innovation, but also on empathy and safety. The Neuroband system can now help detect signs of stress, anxiety and agitation in children with autism. The addition of the GPS functionality enhances safety by allowing caregivers to monitor the child's location in case of elopement. It has demonstrated that the technology can bridge the gap between healthcare and emotional understanding, offering a new level of insight into the wellbeing of children with autism. Ultimately, it represents an important step toward creating intelligent systems to empower parents and healthcare professionals to better provide care globally.

6.2 Recommendations

Based on the findings of this project, some factors can be considered to enhance the design, performance and real-world impact of the system. Regula calibration of sensors such as the MAX30102 and MPU6050 is recommended to improve the consistency of heart rate and motion readings. This would minimize noise and ensure reliable physiological monitoring in different environments. To improve speed of data transmission using more efficient communication protocols or faster GPRS alternatives such as 4G would reduce latency and prevent data loss. Since the system already handles sensitive behavioural and health data, it would be best to adopt advanced encryption standards to protect user privacy during transmission and processing of the data. To manage power consumption, the GPS activity should be triggered in short bursts (e.g. check every five or ten minutes) to save on battery. This prevents overloading the system with coordinates and reducing its operating speed. It would also be advisable to strengthen the cloud infrastructure to support large-scale data collection and analysis. Implementing this would provide valuable long-term insights into behavioural and emotional trends.

6.3 Future Works

Although the system achieved its goal of providing real-time physiological and emotional monitoring for children with autism, several cases can be explored to enhance its functionality, accuracy and usability.

A web-based dashboard could be developed to complement the mobile application, allowing medical professionals to monitor multiple individuals simultaneously. Real-time notifications and alerts to them via email could further improve response times during emergencies. Future prototypes could focus on making the device smaller, lighter and more comfortable for children. Flexible sensors and highly sensitive low-power components could increase wear time and reduce discomfort during daily activities. For long-term field use, conducting large scale-trials would help elevate the system's accuracy, usability and overall impact. Feedback from parents and medical professionals could guide further refinement of the system. Additionally, the flexible nature of the system allows vast application to individuals with similar neurological conditions that would also require continuous monitoring. This includes disorders such as Alzheimer's, ADHD, epilepsy and Parkinson's disease, where physiological tracking can provide early detection of hyperactivity and distress in various contexts.

Ultimately, the future work on the Neuroband project aims to evolve it from a proof-of-concept prototype into an intelligent and practical clinically wearable system. Further research in IoT, artificial intelligence and computing will allow this system to make an even greater contribution to autism care, emotional understanding and personalized health monitoring.

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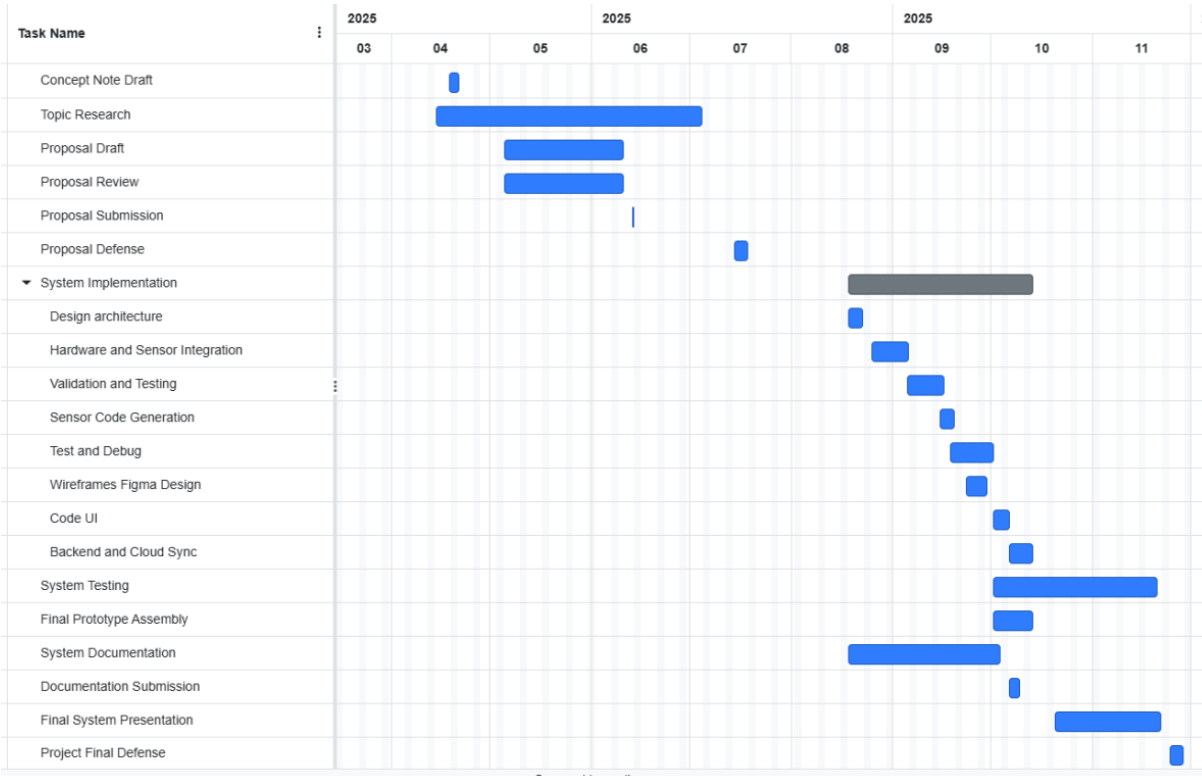
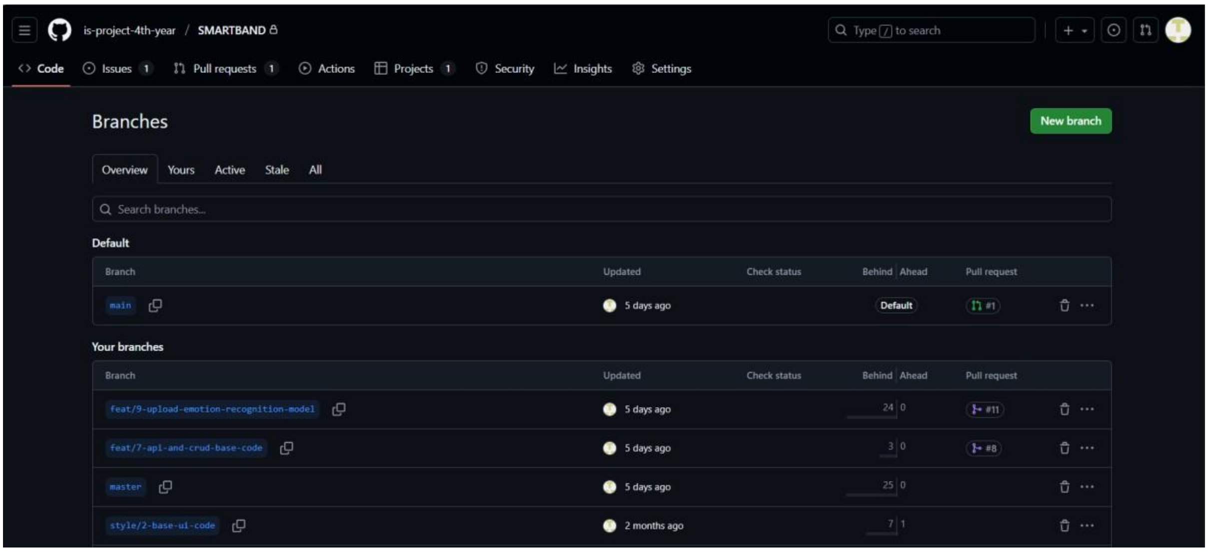
Appendix

Appendix 1: Gantt Chart



Appendix 2: GitHub Branches



Appendix 3: Git Merge