GENE: EARLY DETECTION OF CARPAL TUNNEL SYNDROME USING ELECTROMYOGRAM SENSORS WITH AN APP BASED MONITORING TOOL AND APPLICATIONS OF SUPERVISED MACHINE LEARNING MODEL FOR HOME-BASED HEALTHCARE

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Bachelor of Science in Electronics Engineering

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ABSTRACT

The study introduced the research topic of early detection of carpal tunnel syndrome (CTS) through a wearable device and mobile application. It presents the problem statement, objectives, significance, and scope of the research. The literature review explores previous studies on CTS, wearable devices, and machine learning algorithms, emphasizing the importance of early detection and the potential of wearable technology in CTS diagnosis. The research design and methodology outline a descriptive and developmental approach to prototype development, including hardware design, data acquisition, software architecture, project implementation, and validation. Overall, the study contributed to healthcare technology by offering a novel approach to detecting CTS early using wearable devices and machine learning algorithms.

The findings describe the hardware and software components developed for the project, including a machine learning model. Demographic information from 100 respondents is summarized, emphasizing the prevalence of CTS symptoms. The device, named GENE, shows positive user feedback and high accuracy in classifying CTS cases.

A wearable device using machine learning and EMG sensors detects carpal tunnel syndrome (CTS) early by analyzing muscle activity. It achieved 87% validation accuracy, with the VGG 16 model performing best. Recommendations include improving the mobile app for symptom tracking, gathering a larger dataset, conducting validation studies and trials, and implementing long-term monitoring for CTS management.

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CHAPTER 1

The Problem and Its Background

This chapter provides the study's introduction, background, research gaps, general and specific objectives, significance of the study, scope and limitations, and the definition of terms.

1.1 INTRODUCTION

The human hands are the most active portion of the upper body and are crucial for conducting one's everyday chores. However, repetitive movements over a long period of time can result in overuse syndrome. One of the many complications that can affect the hands is Carpal Tunnel Syndrome (CTS), a musculoskeletal disorder known to cause compression along the median nerve. Carpal Tunnel Syndrome is one of the most prevalent upper extremity disorders. It is the most common compression neuropathy, even though its causes are often difficult to determine. Some contributing factors are strain and repetitive hand activities, vibration, inappropriate wrist posture, trauma, or injuries to the wrists, hormonal or metabolic changes, and changes in blood sugar levels.

Further studies show that the risk of CTS is high in occupations involving exposure to high pressure, high force, repetitive work, and vibrating tools. Additionally, the most susceptible demographic of CTS patients are elderly individuals aged between 40 and 60 years. People with CTS generally experience symptoms such as pain, numbness in the hand and wrist, and tingling sensations that can be felt in the grip distribution area along the median nerves, which are present in the thumb, index finger, middle finger, and the radial side of the ring finger. Additionally, when CTS is left untreated, severe cases can develop, including paresthesia or hand grip weakness, which are typically treated through surgery. In diagnosing CTS, doctors conduct some physical tests, such as Phalen's test and Tinel's sign. Furthermore, the standard medical examinations employed to identify and treat conditions, such as high-resolution hand ultrasounds, X-rays, nerve conduction velocity tests, endoscopy, and electromyography, are costly and invasive in some manner. Immediate diagnosis could be a key to avoiding such invasive treatments and tests to minimize the patient's expenses and discomfort, prevent the need for invasive tests, and reduce the development of severe CTS cases.

The general objective of this study is to develop and design a wearable monitoring device that aims for early detection of CTS using a surface electromyogram that will assess muscle and nerve activity. The project has an application supervised by a machine learning model used for home-based healthcare.

1.2 BACKGROUND OF THE STUDY

Carpal Tunnel Syndrome is a common hand disorder caused by overuse or bad hand posture, which puts pressure on the nerves. There are many tests that can diagnose carpal tunnel syndrome. However, these tests for diagnosing carpal tunnel syndrome tend to be costly, and availability of equipment varies from different hospitals and clinics. Many patients only take these tests when their condition is already severe. Numerous studies have been conducted to create a device that can monitor the hand's condition. In research conducted by Barthakur et al., a microcontroller-based device for real-time and online parameter detection and diagnosis of nerve signals was designed. It implements a voltage-controlled neurostimulator that sends impulses through the targeted nerves. A signal conditioning circuit then processes recorded signals from the neurostimulator for parameter extraction. Subsequently, running the acquired datasets through a cross-validation technique using a MATLAB simulation creates the system's neural network structure, which is implemented in a programmable interface controller (PIC) μC (PIC18F45K22) for online estimation of parameters and diagnosis (Singh A., et al., 2021).

A study by (Piper B., 2017) designed a wrist brace that allows the user to observe the occupational risks that can lead to carpal tunnel syndrome. It is worn while the user performs certain activities to record the range of action allowed by the device to assess the appendage's condition. The device is intended to track and record the angle and posture of the wrist to aid in personal and ergonomic assessment of risk factors associated with CTS.

In a similar study, Michael Mack and Cheol-Hong Min developed a wireless and wearable device that would track the wrist's movement and angle using flex sensors and Arduino. From this, the device can monitor the wrist's angle and correct the wrist's posture to avoid carpal tunnel syndrome. Upon developing this device, the researchers have concluded that a mobile application can be implemented to let the patient see and monitor their hand movements. The study conceptualized a smartphone application for screening for carpal tunnel syndrome, which aims to make data collection and analysis more manageable and accessible by using an anomaly detection algorithm. In this application, the user must follow an object on the screen using only their thumb. The results from the application will serve as input data for the algorithm to process. With this, the study established the relationship between a patient’s difficulty with thumb opposition and carpal tunnel syndrome. The app showed promising results in accurately identifying CTS, displaying a high level of sensitivity and specificity in screening for the condition. This is then used to determine if the patient is more likely to suffer from CTS. Through testing, the application proved to be as effective as physical examinations like Phalen's test and Tinel's sign (Koyama T., et al., 2021).

The researchers created a glove device with embedded pose and muscle sensors and a combination of alert systems to notify the users when they are overusing their hands. The device includes IMU and EMG sensors, a microcontroller, and other components. Additionally, a Force Sensing Resistor (FSR) is responsible for detecting force pressure, an LED indicator that shows how close the user is to overstraining their wrist, and a vibration motor that will give alerts when overworking of the chosen member is present, which corresponds to several LED color changes. The main objective of this study is to monitor wrist movement and notify the user to prevent further strain that may lead to surgical treatment for severe cases of carpal tunnel syndrome. For future work, they suggest considering incorporating the device into a smart-watch system (Ayrapetyan, M., et al, 2021)

1.3 RESEARCH GAPS

Recent studies have shown that there are no surface electromyogram technologies that is accepted for the pre-diagnostics of Median Nerve abnormalities, due to the existing systems' absence of audited and recorded compound muscle action potentials (CMAPs); the use of waveform analysis, which measures the latency near but not at the onset of depolarization; the use of machine learning and prediction-based capabilities; wearability;, crucial physiological factors like patient age and skin surface temperature are not taken into account. Moreover, none of these studies have considered creating a wearable device paired with a mobile application that could detect or diagnose carpal tunnel syndrome in real time once worn. Furthermore, another goal of the project is to find the patterns of early signs of carpal tunnel syndrome through artificial intelligence.

1.4 RESEARCH OBJECTIVES

To develop a wearable device for early detection of carpal tunnel syndrome used in home-based healthcare by implementing surface electromyograms with a mobile application supervised by a machine learning model.

Specifically, it aims to:

1. To develop a microcontroller-based glove that provides the optimal placements of electromyogram probes along with the optimal angle of the hands in order to gather the electrical activity along the median nerves.

2. To formulate a mathematical model using Convolutional Neural Networks to determine healthy and affected patients which will then be connected on a mobile application.
3. To develop machine learning-based application software that will serve as a monitoring tool for the device.
4. To perform a user acceptability test to verify the device's effectiveness.
5. To collaborate with medical professionals in deploying and validating the device.

1.5 SIGNIFICANCE OF THE STUDY

Most people forgo medical check-ups for numerous reasons, which may cause them to fail to recognize problems from which they might already be suffering. For instance, Carpal Tunnel Syndrome is the most frequent entrapment in mononeuropathy problems. Thus, having a wearable device utilized at home for the early diagnosis of carpal tunnel syndrome may help reduce the number of cases, especially severe ones, of CTS when perceived ahead of time.

This research provided a device that is easily accessible at home and is designed to be convenient for the users, offering an application-based monitoring tool for utilization. In addition, the device is considered for fostering self-management and supporting users, workers, and clinicians by providing real-time data that is cost-efficient.

Furthermore, this study is part of Section II-Diagnostics of the authorized Harmonized National Research and Development Agenda (HNRDA) of the Department of Science and Technology. Additionally, this study targets Goal 3: "Good Health and Well-Being", which aims to ensure healthy lives and promote well-being for all at all ages. This goal addresses all major health priorities; this is to ensure that everyone has access to universal coverage, as well as affordable and high-quality detection of Carpal Tunnel Syndrome that is safe and effective.

1.6 SCOPE AND LIMITATIONS

The project focuses on identifying damage or pressure on the carpal tunnel that may give rise to the risk of having carpal tunnel syndrome. The device is not meant to cure damage to nerves but rather an early detection tool, as the objective of this study is to provide a non-invasive and convenient manner for screening carpal tunnel syndrome. The target respondents of this study are Filipino people with carpal tunnel syndrome and those prone to it, such as pregnant women, people with diabetes, office employees, and gamers. The project is deployed in Barangay San Rafael III Noveleta, Cavite.

1.7 DEFINITION OF TERMS

- **Carpal Tunnel Syndrome -** a condition where the median nerve in the wrist becomes compressed, causing pain and numbness.

- **Median Nerve -** a nerve controlling the movement of the fingers, except the pinky, that runs the length of the arm, goes through the passage on the wrist (carpal tunnel), and ends in the hand.

- **Neural Networks -** a network of artificial neurons replicating how a human brain learns.

- **Convolutional Neural Network -** a type of deep learning model specifically designed for analyzing, classifying, segmenting, and processing visual data, using layers that perform convolutional operations to extract meaningful features.

- **Paraplegia -** a person who cannot voluntarily move the lower parts of the body, specifically the lower limbs or lower torso.

- **Electromyogram -** a device that measures a muscle's response to nerve stimulation.

- **Sonography -** a medical ultrasound that allows sonographers or ultrasound technologists to see blood flow through arteries and veins.

- **Machine learning -** focuses on developing algorithms and models that enable computers to learn and make predictions or decisions based on patterns and data, without being explicitly programmed**.** By utilizing historical data, artificial intelligence can be created to forecast outputs.

- **Deep Learning -** a neural network with three or more layers— allows it to determine which features are essential and distinguish which category it falls into.

- **Cross-Validation -** in machine learning is a technique to assess the performance of a model by splitting the data into multiple subsets for training and testing.

- **Validation Accuracy -** measures the quality of the model and how well it can predict new data.

- **Epochs -** the number of the complete rundown of the data to the algorithm.

- **Overfitting -** model fits the training data well but fails in new data it has not seen before.

CHAPTER 2

Review of Related Literature and Studies

This chapter discusses the related literature and studies that are associated with this research.

2.1 Carpal Tunnel

The carpal tunnel, or carpal canal, is a passageway in the wrist that connects the flexor retinaculum to the median nerve. The median nerve is part of the ulnar nerve, which travels from the forearm to the hand. It travels in the flexor retinaculum and synovium on the ulnar side of the wrist and extends to the insertion of the flexor digitorum superficialis muscle on the hand side of the wrist.

The dorsal ligament of the wrist is fusiform and located at the wrist joint (Piper, B. 2017, Gellman, H., 1988).

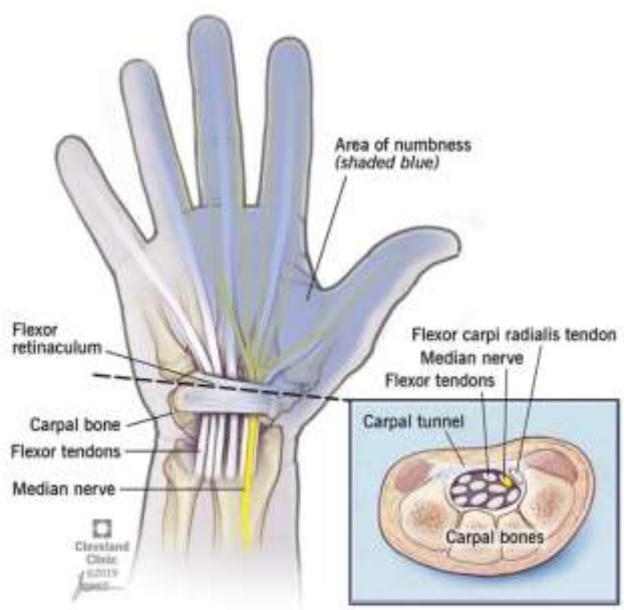


Figure 1. Anatomy of the Carpal Tunnel

This establishes a foundational definition of Carpal Tunnel Syndrome for the study, serving as a guiding principle in the design of the device to enable early detection.

2.1.1 Carpal Tunnel syndrome

Carpal tunnel syndrome is a common condition that affects the hand and wrist, causing pain, tingling, numbness, and weakness in the fingers and thumb. It occurs when the median nerve, which runs from the forearm to the hand, becomes compressed or squeezed as it passes through a narrow passageway called the carpal tunnel. The carpal tunnel is formed by the bones and ligaments of the wrist, and it houses not only the median nerve but also several tendons that control finger movement. Repetitive hand and wrist motions, injury, hormonal changes, and certain underlying medical conditions can contribute to the development of carpal tunnel syndrome. The condition can significantly impact daily activities and productivity, but with appropriate treatment, such as splinting, lifestyle modifications, and, in some cases, surgery, symptoms can be managed effectively. The median nerve provides sensation to the fingers and to the hands. When the median nerve is impinged in the wrist, it may cause numbness, tingling sensation, pain, and other symptoms in the hands and fingers. Carpal tunnel syndrome (CTS) is frequently attributed to the repetitive use of the wrist. CTS symptoms depend on the person. As a result, medical professionals categorized CTS as mild, moderate, and severe. Pain in the hand, numbness, and tingling in the median nerve distribution are all symptoms of the disease. The index finger, middle finger, thumb, and radial side of the ring finger all experienced these sensations (Leung, D., 2014). People with CTS may experience a low quality of life and may need to receive medical treatment due to the discomfort and lack of motor control. Severe carpal tunnel syndrome can cause permanent nerve damage.

Table 1. Summary of Related Studies on Carpal Tunnel

Author	**Year**	**Title**	**Relevant Findings**	**Relationship to the study**
Gellman, H., et al	1988	Carpal tunnel syndrome in paraplegic patients.	Definition of Carpal Tunnel Syndrome and Carpal Tunnel	This provides the medical definition of what carpal tunnel syndrome is.
Piper, B.	2017	Design and Validation of a Smart Brace; Wearable Technology for Carpal Tunnel Syndrome	Anatomy of carpal tunnel	Provides a comprehensive map on the anatomy of carpal tunnel in hands and wrists to build the device
Leung, D.	2014	Carpal Tunnel Syndrome	Carpal Tunnel Syndrome symptoms	Outlines the steps involved in constructing the wearable device utilized in the study.

2.2 Relationship of other Health problems with Carpal Tunnel Syndrome

Extensive research has been done to identify the risk factors for CTS due to the expensive medical and occupational costs. According to research, personal, medical, and occupational factors are the two types of risk factors for CTS. Personal includes age and sex, while medical includes musculoskeletal disorders, having diabetes, and having a higher BMI (Leung, D., 2014).

2.2.1 Carpal Tunnel Syndrome in Men and Women

Several studies have suggested a substantial female prevalence and a peak prevalence around 55 to 60 years since Phalen first described CTS in the 1950s. Women are two to three times more likely than men to have CTS and being older (between 41 and 60 years) raises your odds of developing CTS by about two times (Piper, B., 2017). The main reason why women are more likely to develop CTS is since the average size of a woman's carpal tunnel is much narrower than that of the average man.

2.2.2 Carpal Tunnel Syndrome in Pregnant Women

Carpal tunnel syndrome (CTS) is a common pregnancy problem, with an incidence of up to 62 percent. The feeling of having a tingling sensation and numbness in the index finger, middle finger, thumb, and radial side of the ring finger are the most common symptoms. Wrist pain, and loss of grip strength, are other prevalent symptoms. While not as prevalent, proximal radiation along the volar forearm, medial arm, and shoulder is not uncommon. Forceful activities and extreme wrist positions can aggravate symptoms, which are generally worse at night. It can be diagnosed with high specificity using a combination of history and physical examination. Even when symptoms had not manifested, median nerve activity decreases in nearly all pregnant women throughout the third trimester. Symptomatic treatment often includes activity modification, splinting, edema reduction, and, if necessary, steroid injections. While many women find symptomatic relief after delivery, a considerable number may continue to have difficulties and wear splints for at least three years. In the treatment of these individuals, a high level of vigilance should be maintained.

Forceful activities and extreme wrist positions can aggravate symptoms, which are generally worse at night. It was found that nighttime pains are a common symptom associated with carpal tunnel syndrome. There are various possible causes. Any condition that elevates pressure within the carpal canal or diminishes nerve function can be a potential cause of carpal tunnel syndrome. Alcoholism, diabetes, hypothyroidism, post-traumatic deformity, pregnancy, and rheumatoid arthritis are all illnesses linked to carpal tunnel syndrome. Hormonal changes and edema are the most likely causes during pregnancy. Due to a broad slowing of nerve conduction, gestational hyperglycemia can also play a role. Pregnant women are at higher risk for developing carpal tunnel syndrome (CTS) due to a combination of factors including biological sex, pregnancy, and age. The condition is more prevalent in this specific group due to the influence of these factors. (Ablove, T., et al, 2009).

2.2.3 Carpal Tunnel Syndrome in Old people

This study demonstrates that nerve entrapment in elderly CTS patients is more severe. There are abnormalities in nerve conduction studies in young adults that are associated with weakness, and electrophysiology, but there are no subjective clinical differences, symptoms, or how the hands work. It does not entirely explain the apparent correlation (Blumenthal, S., et al, 2006), but it points to a high incidence of extra brain involvement in the elderly.

The clinical and electrophysiologic aspects of carpal tunnel syndrome (CTS) in elderly people are uncertain. Several evaluations involve age differences in clinical, functional, and electrophysiologic aspects in senior persons referred to neuromuscular testing for evaluation of symptoms suggestive of CTS. The duration of CTS symptoms, hand function, or the prevalence of autonomic symptoms were not distinctive by age. Older individuals showed a higher prevalence of thenar atrophy and weakness compared to younger ones. The elderly individuals had more severe and frequent electrophysiologic abnormalities. Even though there are no age differences in the subjective symptoms of CTS, the study discovered that older people had objective clinical and electrophysiologic evidence of a more severe median nerve entrapment. These demonstrate that objective evidence of CTS severity rather than subjective symptoms should be given more attention when senior patients arrive for a clinical evaluation of the condition. Upon examining the age difference between clinical and electrophysiological CTS, researchers found that the values remained the same when the analysis was restricted to participants with clinically diagnosed CTS.

2.2.4 Carpal Tunnel Syndrome in Paraplegic Patients

In a study published in the Journal of the International Medical Society of Paraplegia, researchers tested 47 paraplegic patients. A total of 94 subjects were included in the study, with motor and sensory nerve conduction of the median and ulnar nerves evaluated, resulting in two sets of data per patient (one person with two hands available). The extent of the spinal cord injury seems to be correlated with the frequency of CTS. The age range of their study was 3 months to 42 years old. 30 patients reported electrophysiological evidence of CTS, compared to 19 patients who had clinical symptoms. According to the data they gathered, CTS and ulnar nerve neuropathy appear to be developing more frequently in the paraplegic population (Aljure, J., et al, 1985).

2.2.5 Obesity as a risk factor for Carpal Tunnel Syndrome

The recent study performed in 2021 at Arba Mich General Hospital shows that among 353 diabetic patients, carpal tunnel syndrome's overall prevalence among people with diabetes was 3.1%. A high body mass index was statistically linked to carpal tunnel syndrome. However, most of the participants, 322 of them, had type 2 Diabetes mellitus. The proponents of the study concluded that a high BMI was significantly but negatively associated with CTS compared to a diabetic person with a normal BMI (Bekele, A., et al, 2022).

Table 2. Summary of Related Studies on Relationship of other Health Problems with Carpal Tunnel

Author	Year	Title	Relevant Findings	Relationship to the study
Piper, B.	2017	Design and Validation of a Smart Brace; Wearable Technology for Carpal Tunnel Syndrome	Carpal Tunnel Syndrome is twice as common in women as to men.	Women will be part of the Data Classification
Ablove, T., et al	2009	Prevalence of carpal tunnel syndrome in pregnant women	CTS is prevalent in pregnant women.	Pregnant Women will be part of the data classification
Blumenthal, S. D., et al	2006	Carpal tunnel syndrome in older adults	Older adults with CTS develop more severe nerve entrapment than younger adults.	Older adults will be part of the data classification
Aljure, J. E., et al	1985	Carpal tunnel syndrome in paraplegic patients	Paraplegic patients have a high risk of developing CTS and ulnar nerve neuropathy	Paraplegic patients will be part of the data classification
Bekele, A. A., et al	2022	Prevalence and Associated Factors of Carpal Tunnel Syndrome Among Diabetic Patients in Arba Minch General Hospital, Southwest Ethiopia,	BMI has a negative correlation with CTS. Diabetes has a positive correlation with CTS.	Diabetic people will be part of the medical data classification.

2.3 Relationship of Hobbies and Occupation to Carpal Tunnel Syndrome

2.3.1 Correlation of Carpal Tunnel Syndrome with usage of computers

There has been a debate regarding the relationship between computer usage and musculoskeletal symptoms, particularly Carpal Tunnel Syndrome (CTS), which is common among computer users. This study aims to investigate the association between CTS and the use of computer keyboards and mice among male professionals working in information technology, encompassing young, adult, and middle-aged individuals. Statistical methods were employed to analyze the data and examine the potential connection between CTS and computer use. The study involved a sample of one hundred individuals selected through random sampling, and the data were analyzed using SPSS software, with the results presented in pie charts. The participants ranged in age from 18 to 65 years and predominantly consisted of IT workers who possessed some knowledge of carpal tunnel syndrome and its effects. The findings of the study indicate that computer use does not pose a significant occupational risk for developing symptoms of carpal tunnel syndrome. However, there is evidence suggesting that occupational factors may influence the occurrence of CTS. (Shiri, R., et al, 2015).

2.3.2 Carpal Tunnel Syndrome in Office Jobs

The occupational risk factors were not adjusted for in studies that contrasted computer professionals with the general population or with other occupational groups. Therefore, office workers who rarely or never use computers are a better comparison group than the general population or several professional classifications. The results of this meta-analysis suggest that excessive computer use, especially mouse use, may represent a minor occupational risk factor for CTS. Additional prospective studies among office workers with objectively assessed keyboard and mouse use and CTS symptoms or indications supported by nerve conduction testing are required (Shiri, R., et al, 2015).

Table 3. Summary of Related Studies on Relationship of Hobbies and Occupations to Carpal Tunnel

Author	Year	Title	Relevant Findings	Relationship to the study
Shiri, R., et al	2015	Computer use and carpal tunnel syndrome: A meta-analysis	Prolonged use of computers may cause symptoms of CTS. only, and may not injure median nerve.	The causation of prolonged computer use matches the symptoms of Carpal Tunnel Syndrome
Falah-Hassani, K., et al	2015	Computer use and carpal tunnel syndrome: A meta-analysis	Studies of office workers show a weak but potentially meaningful positive association between computer use and CTS.	Office workers will be part of the physical data classification

2.4 Existing Methods and Devices in Detecting and Diagnosing Carpal Tunnel Syndrome

2.4.1 Diagnosing Carpal Tunnel Syndrome

A variety of diagnostic tools can be used to detect carpal tunnel syndrome and other peripheral neuropathies. Nerve conduction studies are electronic procedures that measure the amplitude and velocity of action potentials passing along a nerve to determine its health. The action potentials are produced by applying a high voltage to the nerve. The high-voltage stimulus's form, duration, and amplitude are all carefully chosen to ensure that the stimulus is both safe and effective. Nerve conduction examinations are usually thought to be accurate and dependable. They are, however, extremely complex and expensive. A stimulus device and two basic electrical devices to detect peripheral neuropathies were created and tested during this study. Both testing equipment used the stimulus device to create nerve action potentials. The first device captured nerve action potentials and used them to measure nerve health. The second gadget measured the motor response of a digit following stimulation to assess nerve health. Neither of the two testing devices was able to accurately determine nerve health in the end. However, a useful stimulus device has been created. Both the median and ulnar nerves were able to be stimulated with this device (Theses, M., et al, 2018).

This study confirms that nerve conduction tests are not only safe and effective but also accurate and reliable. For this reason, the project will utilize EMGs, or electromyogram testing, as input for the algorithm to analyze the probability of the user acquiring CTS, or carpal tunnel syndrome.

2.4.2 Electrodiagnostic testing

Several tests have been done using the carpal compression test, which is a new procedure that involves applying direct pressure to the carpal tunnel and the underlying median nerve. The results of the Tinel Sign, the Phalen test, and the novel test were assessed in 31 patients (46 hands) who had carpal tunnel syndrome confirmed electrodiagnostically, as well as a control group of 50 people. For the diagnosis of carpal tunnel syndrome, the carpal compression test was found to be more sensitive and specific than the Tinel and Phalen tests.

The gold standard for diagnosing CTS has been electrodiagnostic testing for many years now. As stated in a study by the Department of Neurology, University of Virginia Health Sciences Center, School of Medicine, Charlottesville, Virginia.

Electrodiagnostic testing is the process of measuring the electrical activity of a muscle or nerve. The electrical signals that are created from these can be slowed or stopped if they are affected by injuries or diseases. However, despite the accuracy of the tests, they can be uncomfortable for the patient since the main procedures of electrodiagnostic testing are electromyography and nerve conduction studies, which include intrusive methods such as the insertion of a fine needle electrode into specific muscles to measure their electrical signals. The research aims to provide a device that is not only accurate for diagnosing but also comfortable for the patient by removing intrusive methods during the data gathering procedure (Durkan, J.A., 1991).

2.4.3 Electromyogram

By reviewing the data of the Electromyography Laboratory for the year 1994, the authors investigated the use patterns of electrodiagnostic testing at the University of Virginia. CTS studies accounted for 15% of the 1626 studies conducted during that time. The mononeuropathy was usually mild, and most of the patients were referred to specialists for testing. Primary care physicians had a distinct referral bias, with the severity of mononeuropathy in individuals they referred for testing being considerably higher than in patients referred by specialists. Electrodiagnostic testing offers a clear significance in the examination of patients with upper-extremity symptoms, according to the findings. Despite this, primary care providers appear to use electrodiagnostic testing rarely (Phillips, L.H., et al, 2008).

A needle EMG was used in electrodiagnostic testing for the study conducted by Lawrence H. Philips II, M.D., and Vern C. Juel, M.D. examined the upper-extremity muscles in locating neuropathic causes. In relation to this study, surface EMG was used to measure the electrical activity passing through the nerves.

2.4.4 Ultrasound

Since it may identify alterations in the median nerve's shape and rule out anatomical variations and space-occupying lesions such ganglion cysts and tenosynovitis, ultrasonography (US) is a valuable method for confirming the diagnosis of carpal tunnel syndrome (CTS). A study comprised 233 CTS patients who were diagnosed by clinical and electrophysiological (NCS) testing. Cross-sectional area, flattening ratio, and neural Power Doppler (PD) signals were among the US measurements taken at the tunnel intake. Patients with severe NCS results or neurological impairments were referred for open surgical decompression; the rest were offered the option of conservative or surgical treatment. The primary outcome variable was a 70% improvement in CTS symptoms. Baseline, one week, one month, and six months after treatment were all assessed. The neural vasculature was found to have an inverse relationship with the NCS severity of CTS ($r = 0.648$). The US measures improved after one week in CTS cases treated conservatively; however, there was an initial phase of post-operative nerve measure rise in the surgically treated cohort before settling at 1-month follow-up. The settled measures were taken with the following goals in mind: 1. Before and after the management of CTS patients, ultrasonography was used to examine the median nerve and its neurovascular blood flow. 2. Examine whether baseline US parameters can be used as a biomarker to predict future outcomes and help CTS patients develop a treatment strategy.

Patients with a high median nerve flattening ratio had a significantly greater risk of poor outcomes (RR 3.3). Nerve flattening was related to a longer duration of illness (RR 4.3) and a low PD signal in the cohort with nerve flattening (RR 4.1). In addition to the diagnostic usefulness of US in CTS, the identification of enlarged median nerve neurovasculature has a good prognostic value as a sign of early median nerve affection, according to the findings. Although ultrasound is one of the most used methods for testing to identify whether a patient has carpal tunnel syndrome, it is expensive. This study plans to create a device that is accessible and affordable for everyone by its utilization of non-invasive techniques and readily available equipment, eliminating the need for expensive ultrasound machines and specialized training, making it more accessible and cost-effective for both patients and healthcare providers. (El Miedany, Y., et al, 2015).

2.4.5 Sonography

Sonography, also known as ultrasound imaging, is a non-invasive medical imaging technique that utilizes high-frequency sound waves to create real-time images of internal structures and organs within the body. Sonography can also be used as a diagnostic tool in evaluating carpal tunnel syndrome (CTS) due to its high-frequency sound waves which are used to produce real-time images of the body's internal structures. The study conducted by Swen, W.A et al, was to see how useful sonography (SG) conducted by a rheumatologist is in diagnosing carpal tunnel syndrome (CTS). The researchers looked at 63 patients who had clinical symptoms of CTS, as determined by the neurologist based on patient history and clinical examination. A rheumatologist performed SG and reviewed the nerve conduction study (NCS) six weeks before surgery. Improvement of 90 percent or higher in initial complaints three months after surgery was considered the post-hoc gold standard for CTS diagnosis.

Results show that after surgery, 47 patients (75%) reported a 90% reduction in their problems. Patients with CTS had a median nerve cross-sectional area of 11.3 mm2, compared to 6.1 mm2 in the control group.

Table 4. Test results between using sonography and nerve conduction study.

	Sensitivity	Specificity	Positive Predictive Value	Negative Predictive Value	Accuracy
Sonography	0.70	0.63	0.85	0.42	0.68
Nerve Conduction Study (NCS)	0.98	0.19	0.78	0.75	0.78

The table compares the detection performance of two methods, SG (method 1) and NCS (method 2), for detecting CTS (Carpal Tunnel Syndrome). SG is less sensitive than NCS in detecting CTS, meaning it may miss more true positive cases. However, SG is more specific, meaning it is better at ruling out individuals without CTS. The positive predictive value is slightly higher for SG, indicating that a positive test result from SG is more likely to indicate the presence of CTS. However, NCS has a higher negative predictive value, suggesting that a negative test result from NCS is more reliable in excluding the presence of CTS. Overall, NCS appears to have better performance in detecting CTS based on the given data.

This method of testing is fairly accurate and uses image-displaying techniques to identify whether the patient has carpal tunnel syndrome; however, it is more expensive than other available methods. This study plans to create a device that is accessible and affordable for everyone (Swen, W.A., et al, 2001).

2.4.6 Wearable Technology

The piece describes early research and development of a wireless wearable wrist position detection device that uses sensors and a microcontroller-based Bluetooth wireless communication system to monitor and track deteriorating symptoms of carpal tunnel syndrome. The proposed system monitors changes in wrist posture using flex sensors. Corresponding voltage levels are A/D converted, sent to a computer, displayed, recorded, and then examined to determine the wrist's location. The suggested solution offers a minimally invasive, non-invasive method for long-term mobile wrist posture monitoring. The suggested device also includes a feedback system to alert the user to aggravating circumstances. However, it simply keeps track of the angles of the joints where the device is worn, which is insufficient to identify early carpal tunnel syndrome symptoms (Mack, M., 2019). The purpose of the study is to determine how likely it is that the patient has carpal tunnel syndrome.

2.4.7 Artificial Intelligence

Studies conducted by Goto S. et al. had shown that the symptoms of rare diseases like cardiac amyloidosis (CA) resemble those of more common disorders; it can be challenging to identify patients with these conditions. The delayed diagnosis of this ailment has limited the use of approved treatments for CA. Artificial intelligence (AI) is used to aid in identifying rare diseases. Here, The Authors of the thesis demonstrate an AI-based pipeline for CA identification that uses electrocardiograms (ECG) or echocardiograms as input data. These models, which were developed and tested at three and five academic medical centers (AMC), respectively, have C-statistics of 0.85 to 0.91 for ECG and 0.89 to 1.00 which match with known values for diagnosing CA for echocardiography that allow them to identify CA. The ECG model had a positive predictive value (PPV) of 3–4% at 52–71 percent recall after being deployed virtually on two AMCs. The performance of the echocardiography [ECG] model at 67 percent recall is improved from a PPV of 33 percent to a PPV of 74–77 percent when pre-screening using ECG. Finally, the Author of this Thesis had developed an automated method to improve CA detection, which ought to be transferable to other uncommon cardiac conditions. The study's simulation of any prospective alterations in the patient's body will greatly benefit from the image identification capabilities of artificial intelligence (Goto, S., et al, 2021).

2.4.8 Automatic Electrodiagnosis using machine learning

The relevance and necessity of nerve conduction investigations in the treatment of carpal tunnel syndrome have been the subject of extensive dispute, according to a recent study by Tsamis, K. I. et al, the purpose of this study was to assess the potential for automatic diagnosis of median nerve mononeuropathy based on electrodiagnostic markers and decision-making regarding carpal tunnel syndrome using both distinctive features chosen based on physiology and mathematics and standard electrodiagnostic criteria, which are frequently used in clinical practice. 38 participants in the study were evaluated prospectively. The researched factors were combined using machine learning techniques to produce a consistent and accurate diagnostic. When compared to clinical diagnosis and traditional neurophysiological diagnosis made by doctors using nerve conduction testing, automatic electrodiagnosis had an accuracy of 95% and 89%, respectively. The findings imply that automatic diagnosis of carpal tunnel syndrome is feasible and that it can be used in decision-making to eliminate human error. Additionally, it has been demonstrated that the unique traits investigated can be employed to detect the syndrome in addition to the ones that are already in use, increasing the procedure's accuracy (Tsamis, K.I., et al, 2021).

The possibility of implementing machine learning for clinical electrodiagnostic testing, which was used in the proposed research, is the primary emphasis of the project. With this, the device's performance will significantly increase in terms of accuracy as well as speed of result retrieval.

2.4.9 RNN (Recurrent Neural Network) for EMG-Based Diagnosis

Carpal tunnel syndrome was confirmed in 48 wrists through electrodiagnostic studies by Ilbay, K. et al, A measurement of 11 mm^2 for the cross-sectional area (CSA) of the median nerve was used to indicate swelling. When compared to electrodiagnostic testing, swelling of the median nerve showed the highest level of accuracy (89%) among the grayscale sonographic criteria. Among all the sonographic criteria, the presence of hypervascularization in the median nerve had the highest accuracy (94%). Median nerve swelling and the bending of the flexor retinaculum had accuracies of 81% and 77% respectively. Color Doppler sonography was found to be more precise than grayscale sonography in detecting median nerve involvement in patients suspected of having carpal tunnel syndrome, particularly through the identification of intraneural hypervascularity in the median nerve (Ilbay, K., et al, 2021).

2.4.10 Deep Learning Model

Many people who work in manual material handling (MMH) are subjected to strenuous physical demands linked to work-related musculoskeletal disorders (WMSDs). The physical demands of a profession must be quantified to be hired for and compensated for injuries, which is crucial for identifying high-risk positions. Experts today do most of the physical demand analysis (PDAs) utilizing semi-quantitative and observational methods.

The lack of precision and dependability could be an issue, especially when trying to determine boundaries during the return-to-work period. In addition, the effectiveness of the work restrictions versus adherence to them is muddled since there is no method to verify adherence to them when a person returns to work on modified duty. The Researchers used data from eight inertial measurement units (IMUs) and a deep learning model to forecast 15 occupational physical activities to resolve this. Predicting isolated occupational physical activity overall was 95% accurate. Accuracy varied significantly (0–95%) when applied to more challenging tasks that include occupational physical activities (OPAs). When combined with simulated task assignments, more work is required to accurately predict OPAs (Yan, Y., et al, 2021).

2.4.11 Microcontroller-based voltage-controlled neurostimulator

The use of these embedded systems in healthcare analytics and medical diagnosis is inevitable. The article by Singh, A. et al. on Microcontroller-Based Online Nerve Parameter Estimation for Diagnosis of Healthy Subject Using Real-Time Nerve Conduction Study Signal Acquired Using Voltage Controlled Neurostimulator describes the development of an online parameter detection and diagnosis system using real-time nerve signals and a microcontroller (C). The device is designed with a low-cost, low-power voltage-controlled neurostimulator to stimulate the desired areas of the underlying nerve. A signal conditioning circuit is built in the second stage to precisely handle and gather the recorded signals for parameter extraction.

The best neural network structure is chosen using a dataset of pre-diagnosed nerve signals in MATLAB simulation in offline mode, and it is then implemented in a programmable interface controller (PIC) C (PIC18F45K22) for real-time parameter estimation and diagnosis. Then, utilizing embedded, programmed C, nerve signals are examined by many lab participants using the guidelines of the traditional nerve conduction study (NCS). The outcomes of the tests and subsequent comparison with cutting-edge designs show that the recommended approach for the online detection of NCS parameters and subsequent diagnosis is viable and reliable (Singh, A., 2021).

2.4.12 Smartphone-based application for screening carpal tunnel syndrome

Early detection is crucial in treating carpal tunnel syndrome. Physical tests such as Phalen's test and Tinel's sign are commonly performed to check if the symptoms the patient is experiencing are caused by carpal tunnel syndrome. However, the sensitivity is not high, which means they are still susceptible to errors. Fujita et al. created a smartphone application that allows easier access, data collection, and analysis using an anomaly detection algorithm. It was intended for screening and the detection of carpal tunnel syndrome. In this application, the user is required to follow an object on the screen using only their thumb. The algorithm will analyze the data based on the user's performance and generate an output from that. The study was able to establish the relationship between a patient's difficulty with thumb opposition and carpal tunnel syndrome and used this to determine if the patient was more likely to suffer from CTS. Through testing, the application was proven to be as effective as physical examinations like the Phalen test and Tinel sign. (Koyama, T., et al, 2021).

Table 5. Summary of Related Studies on Existing Methods and Devices in Detecting and Diagnosing Carpal Tunnel Syndrome

Author	Year	Title	Relevant Findings	Relationship to the study
Svendsen, P.	2018	Development of Electronic Testing Devices That Detect Peripheral Neuropathies	Nerve conduction examinations are generally accurate and dependable.	Nerve conduction is one of the methods implemented in the study.
Durkan, J. A.	2008	A new diagnostic test for carpal tunnel syndrome	The gold standard of diagnosing CTS has been Electrodiagnostic testing for many years now.	Electrodiagnostic testing is one of the procedures implemented in the study.
Phillips, L.H., et al	2008	The role of electrodiagnostic testing in carpal tunnel syndrome	Electrodiagnostic testing offers a clear significance in the examination of patients with upper-extremity symptoms	One of the technologies that is used in the study is electrodiagnostic testing. And shows the viability of electrodiagnostic testing
El Miedany, Y., et al	2015	Ultrasound assessment of the median nerve	Ultrasound is useful in examining CTS and is used by doctors to detect CTS as of today.	Ultrasound is one of the tests that can validate the presence of CTS from the data classification.
Wijnand A.A., et al	2001	Carpal Tunnel Sonography and Nerve Conduction Study	Sonography is another viable option for detecting CTS.	Sonography is another viable option that can be implemented if available kits have been made for the public use.
Mack, M., et al	2019	Design of a Wearable Carpal Tunnel Syndrome Monitoring Device.	The use of wireless wearable wrist position detection device detection system that monitors CTS.	Wireless wearable device detection system with sensors and microcontroller-based wireless (Bluetooth) communication system.

Keith M., et al	2009	Diagnosis of Carpal Tunnel Syndrome	There are many tests to diagnose carpal tunnel and could be used for further testing to improve the study.	Strengthening the need for a home-based CTS diagnostic tool
Goto S., et al	2021	Artificial intelligence-enabled fully automated detection of cardiac amyloidosis using electrocardiograms and echocardiograms	Implementing AI for detection of problems which will be implemented in the study.	Artificial Intelligence is a technology that is to be implemented in the study.
Tsamis K., et al	2021	Automatic electrodiagnosis of Carpal Tunnel Syndrome Using Machine Learning	Attests the feasibility of applying machine learning in clinical electrodiagnostic testing.	Automation in electrodiagnosis is implemented in the study
Ilbay K., et al	2011	A New Application of Recurrent Neural Networks for EMG-Based Diagnosis of Carpal Tunnel Syndrome	Different models that could be used in the study	Recurrent neural networks would be one of the possible models of the study
Yan Y., et al	2021	Applying wearable technology and a deep learning model to predict occupational physical activities	An attempt at a wearable technology that is close to the study but aims to solve a difference problem	Wearable Technology is the design of the study
Singh A., et al	2021	Microcontroller-Based Online Nerve Parameter Estimation for Diagnosis of Healthy Subject Using Real-Time Nerve Conduction Study Signal Acquired Using Voltage Controlled Neurostimulator	The use of microcontrollers for diagnosis that is also implemented in the study	Microcontrollers is one of the systems to be implemented in the study
Koyama,T., et al	2021	A Screening Method Using Anomaly Detection on a Smartphone for Patients with Carpal Tunnel Syndrome: Diagnostic Case-Control Study	The use of a mobile application for screening carpal tunnel syndrome.	A mobile application will be implemented in the study

2.5 Prevention of Carpal Tunnel

2.5.1 Objective Measures and Splint Use

In a study by Gellman, H. et al, a total of 105 adults with carpal tunnel syndrome (CTS) were evaluated to determine the efficacy of a neutral-angle wrist splint and establish referral criteria. Descriptive and inferential statistics were used to examine the observations of ten subjects before and after therapy. After using the splint, 67% of the participants reported symptom improvement. A T-test comparison of sensory latency values before and after therapy revealed improvement for the entire group. There was a lack of significant differences between relief and no-relief groups when comparing: gender, neuromuscular integrity, and presiding symptoms; the time before treatment; age; duration of pre- and post-treatment sessions; and the response time of motor and sensory fibers. The motor delay showed a substantial difference; the relief group improved, while the no-relief group declined. Splinting appears to be most effective when performed within three months of symptom onset, according to research. Splinting was least effective for those who had injuries to the wrist structures or the median nerve (Gellman, H., et al, 1988).

The efficacy of wrist splints was analyzed in this review of the literature for clinical intuition. However, the proposed study is a wearable glove device that will detect early signs of carpal tunnel syndrome and assess the probability of a person possessing the said musculoskeletal disorder (Kruger, V.L., et al, 1991).

2.5.2 Smart Braces

To discover occupational risk factors for repetitive strain injuries like carpal tunnel syndrome, Bryan Piper's study developed and validated a wrist brace that can track movement data. The brace had special sensors positioned at specific points on the wrist joint. 13 participants wore braces while performing daily activities, and their movement data was also collected using VICON motion capture technology. Various metrics were compared for each activity, including range of motion, average angle, peak and average velocity, and mean acceleration. The measurements from the brace were similar to those from VICON, and both methods could differentiate between tasks based on the collected data. This proof-of-concept brace has implications for recording occupational risk factors for carpal tunnel syndrome and for evaluating ergonomics. It also opens possibilities for future assessment methods. (Piper, B., 2017).

2.5.3 Over-Use Warning Glove

A wearable glove technology was designed by Ayrapetyan et al. to monitor the posture and pressure on the wrist. It implements an inertial measurement unit, electromyogram sensors, a microcontroller, and LEDs. The device was worn by the user while performing different tasks to continuously check the condition of the wrist and send an alert when there are signs of overuse (Ayrapetyan, M., et al, 2021).

Table 6. Summary of Related Studies on Prevention of Carpal Tunnel Syndrome

Author	Year	Title	Relevant Findings	Relationship to the study
Kruger, V. L., et al	1991	Carpal Tunnel Syndrome: Objective Measures and Splint Use	The study aims to use splints to prevent carpal tunnel	A splint like frame could be implemented on the design to get a more controlled data
Piper, B.	2017	Design and Validation of a Smart Brace; Wearable Technology for Carpal Tunnel Syndrome	The study focuses on using a smart brace as an aid for ergonomics.	Braces could be a possible proponent to be implemented
Ayrapetyam, M., et al	2021	Over-Use Warning Glove for Carpal Tunnel Syndrome	The study aims to develop a device that alerts the user preventing overuse of the hand.	is another method for recognizing possible damage and overuse of the chosen member.

2.6 Interpretation of Data

2.6.1 1D Convolutional Neural Network

The 1D Convolutional Neural Network (1D CNN) became one of the most advanced methods for signal processing applications such as structural health monitoring, anomaly detection in electronic circuitry, motor fault detection, and many more. In this study, 1D CNN was used given its several benefits of utilizing an adaptable and compact method to get a predictable outcome. Additionally, It can be used without any pre- or post-processing, such as feature extraction, selection, dimension reduction, etc., on raw signals. In addition, compared to the needs of 2D deep CNNs, compact 1D CNNs can be trained with smaller data sets. Real-time and inexpensive hardware can be implemented using 1D CNN's straightforward and compact design, which merely conducts linear 1D convolution. (Kiranyaz, S., et al, 2019).

2.6.2 Biomedical Signals

An electromyogram (EMG) signal can be used to study and quantify how a muscle reacts to a nerve's stimulation both during contraction and relaxation. It can also be used to spot abnormal nerve and muscle activities that are brought on by different neuromuscular conditions. A surface EMG electrode that has been used in the study collects the sum of activated motor neurons.

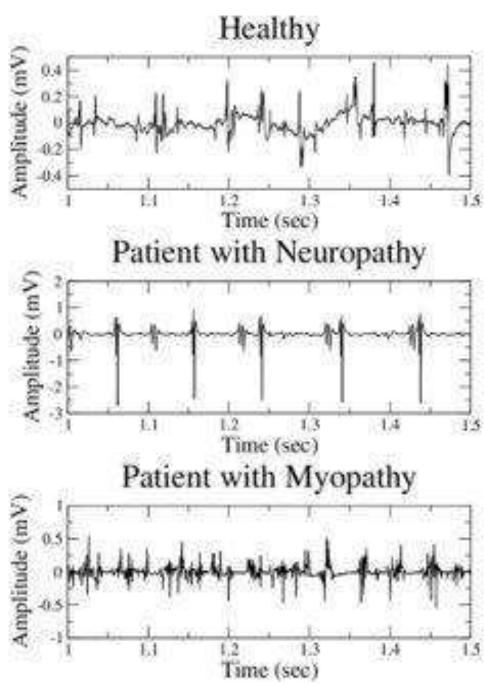


Figure 2. EMG signals of Healthy subject, Patient with Neuropathy, and Patient with Myopathy (Hussien, A., et al, 2016)

Neuromuscular disorders are divided into neuropathy, which results in motor neuron degeneration, and myopathy, which damages the muscle fibers and causes dysfunction of the muscles (Hussien, A., et al, 2016). A study by Hussein et al. provides the EMG signals in each case with the addition of healthy signals, as shown below.

Table 7. Summary of Related Studies on Interpretation of Data

Author	Year	Title	Relevant Findings	Relationship to the Study
Kiranyaz, S., et al	2019	1-D Convolutional Neural Networks for Signal Processing Applications	The study will use 1-D CNN to process data for the software.	The application of convolutional neural networks in health monitoring.
Hussien, A., et al	2016	Tracking of Medical Muscular Activities for Identification of Human Motor Disability using Electromyogram Biomedical Signals (EMG)	Distinction of EMG readings between healthy and affected patients.	The use of Electromyogram (EMG)

2.7. Hardware Material

2.7.1 Fabric Material

The study's wearable device is intended to be worn by its users. Due to this, the building of the device must conform to having a simple UI, ease of use in wearing, and no overly complicated steps and procedures. Attached to it are the electromyogram sensor probes and circuit board. One of the goals that the researchers aim for is to properly insulate the device from electric conductivity to prevent inaccurate readings of the sensors. Hence, nylon and garter fabric are used for the device, considering that nylon prevents the unwanted flow of current, making it an excellent electrical insulator (Aljamali, N., et al, 2021).

Table 8. Summary of Related Study on Hardware Material

Author	Year	Title	Relevant Findings	Relationship to the Study
Aljamali, N., et al	2021	Types of Electrical Insulators and their Electrical Applications	Nylon is one material that can be used as an insulator.	Wearable devices in this study used nylon fabric material.

CHAPTER 3

Methodology

This chapter provides the research design, process flow, hardware development, data acquisition, software architecture, project implementation and validation, statistical analysis, and project work plan.

3.1 Research Design

The study used a descriptive and developmental research design.

Input	Process	Output
Software Requirements: • Python • Arduino IDE • Visual Studio • Kodular • Fusion360 **Hardware Requirements:** • Arduino Nano • Arduino EMG Kit • Electromyogram sensors Kit • Transceiver Module **Knowledge Requirements:** • Python Programming (Machine Learning, Deep Learning) • Electronic Calibrations • Medical Readings (EMG) • Front-end, Back-end Mobile Application • PCB Design • Soldering • 3D Design and Printing	**Hardware Development:** - Develop a microcontroller-based glove that provides the optimal placements of electromyogram probes **Software Development:** - Formulate a mathematical model using Convolutional Neural Network - Develop machine learning-based application software **Testing:** - Conduct a User Acceptability test - Software and Hardware compatibility testing - Implement and validate the device in collaboration with a medical professional.	**Early Detection of Carpal Tunnel Syndrome using Electromyogram Sensors with** an **App Based Monitoring Tool and Applications of Supervised Machine Learning Model for Home-based Healthcare**

Figure 3 - IPO Diagram

The diagram involves the development of the wearable device for early detection of carpal tunnel syndrome, which is intended to be accomplished along with a mobile application, as well as methodical plans. Below are the summaries of the input parameters, the processes, and the expected output of the study.

After the frame is constructed using glove and garter straps, three electromyogram probes are placed in the palm, forearm, and elbow areas, which is attached to the skin using disposable EMG patches. The probes are then connected to a separate circuit board enclosed by a 3D-printed case, which holds the Arduino Nano connected to the EMG module, three 9V batteries, and the Wi-Fi module, which sends the collected data to the mobile app.

To help interpret the data results, a machine learning model is encoded to generate predictions and pre-diagnosis of carpal tunnel syndrome through a convolutional neural network (CNN). Following this, a mobile app is assembled to connect to a wearable device responsible for recording data and notifying the user of the health status of their hands when the device is used.

3.1.1 Developmental Research

Developmental research is an effective methodology that includes a systematic process of designing, developing, and evaluating innovative educational products and programs using instructional technology. This study embodies developmental research, as the main goal is to design and develop a prototype of a wearable device with technology that will detect early signs of carpal tunnel syndrome.

3.1.2 Descriptive Research

The descriptive research method is also present in this to accurately diagnose findings relating to carpal tunnel syndrome. Additionally, one of the objectives of this study is to perform a user acceptance test (UAT) to evaluate whether the actual software application is functional and able to manage the data from the wearable device transmitted wirelessly to the user's mobile device. The results were analyzed using descriptive statistics. Furthermore, in collaboration with a medical professional, this research was done in a normative type of study as per their suggestion.

3.2 Research Process Flow

This section presents the major steps that will be accomplished in order to complete this research study:

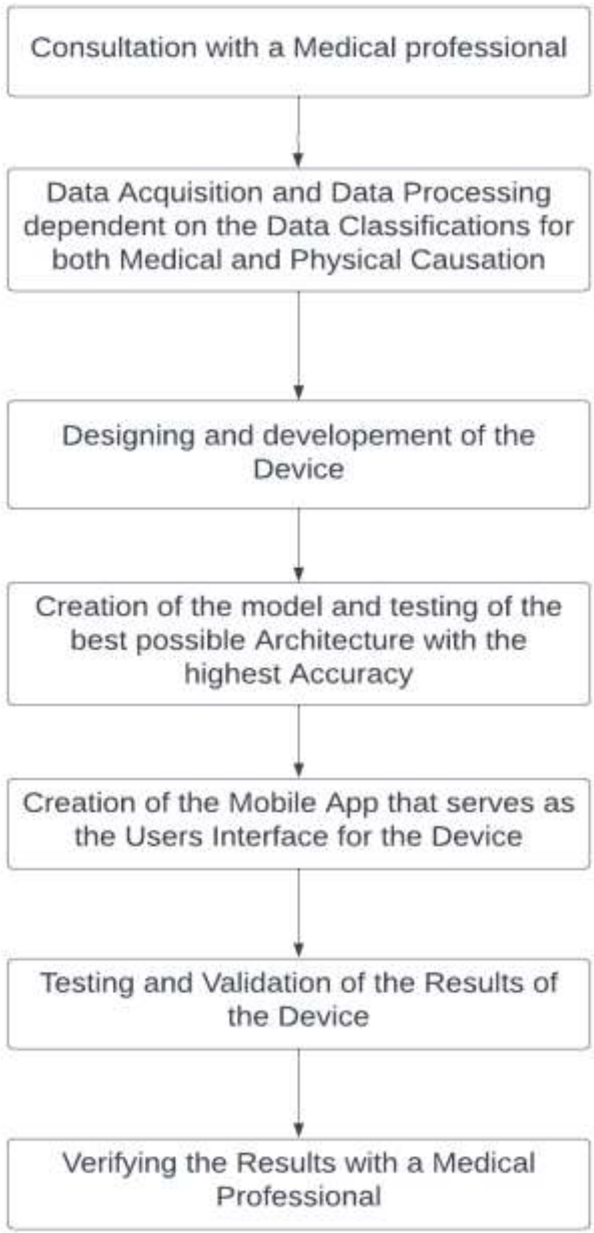


Figure 4. Research Process Flow

The figure above shows the flow of the steps to accomplish the study. The process is divided into seven parts: initial consultation, data acquisition, development of the device, development of the AI model, mobile application creation, testing, and verification. For the first part, consultation with a medical professional is needed to validate the study. After verification of the study, several datasets are needed for the software and mathematical model. Data demographics are requested from the proponents of the study. During this step, data acquisition from the hardware is also initialized. After the acquisition of all the data from the device and the proponents of the study, the chosen model architecture is constructed. With that in mind, the device would need a user interface to see the results, so a mobile application was developed. This application provides the findings and necessary information on how to proceed with their readings. Finally, the results from these tests are validated by medical professionals in the given field to determine the accuracy of the device. This is done so the device can provide comprehensible readings to the user.

3.3 Development of Wearable Device Integrating Electromyogram

This section will be the hardware development, which includes the materials and equipment needed; the design of the wearable device; and calibration and tuning of the electromyogram.

3.3.1 Materials and Equipment

The attached components on the wearable device for the early detection of carpal tunnel syndrome are the Arduino nano, electromyogram sensor kit, and transceiver module. In addition, a mobile phone is involved, as it is a tool where the application is displayed.

3.3.2 Design of the Device

The base of the wearable device is a nylon glove, and attached to it are adjustable garter straps that allow the device to accommodate a wide variety of hand sizes. The EMG will send small electrical signals from the forearm to the palm to detect if there are abnormalities in the fluctuations of waves in the nerves. The program will be run through the Arduino Nano and sent to the mobile device via the Wi-Fi module, both of which are wired through a circuit enclosed in a 3D-printed case along with the EMG module.

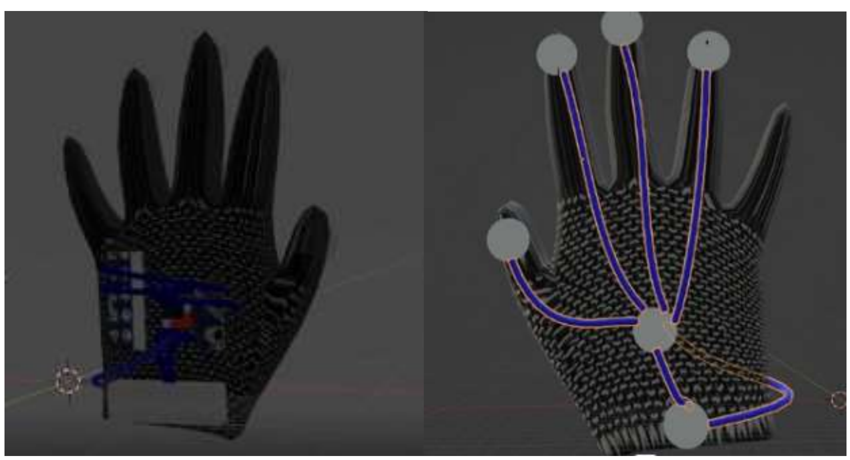


Figure 5. Initial 3D Design of the Wearable Device

The figure above illustrates the initial design of the glove device which served as the foundation for the innovation of early detection of Carpal Tunnel Syndrome combining with sleek aesthetics to enhance the user experience.

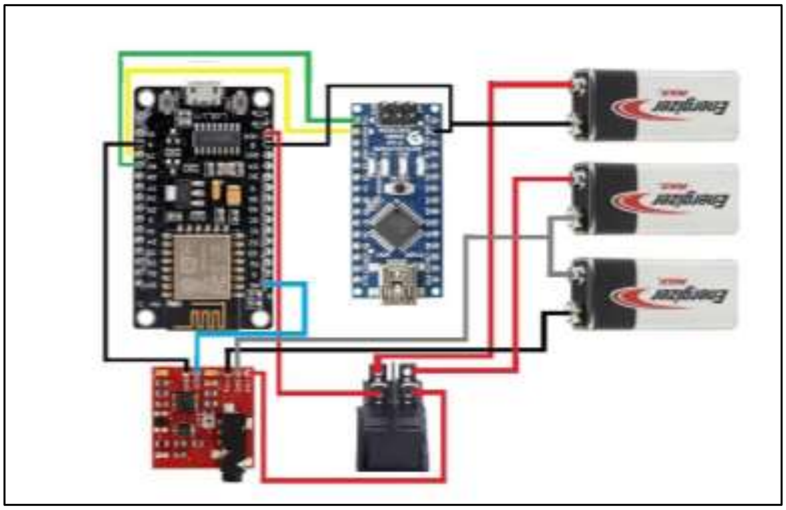


Figure 5.1. Circuit Diagram

The circuit diagram above illustrates the intricate network of components and connections in the initial design of the wearable device, showcasing the integration of Arduino Nano, Electromyogram sensor, switch, batteries, and Wi-Fi module for accurate and real-time monitoring of Carpal Tunnel Syndrome.

3.3.3 Calibration and Fine Tuning of the Electromyogram

This procedure enabled the researchers to optimize the structure of components attached to the wearable device. In this case, identifying the optimal placement for the electromyogram probes, as well as locating which part would give the most accurate signal reading for the results, will enhance the quality of the device. For this part, the researchers consulted different professionals and conducted numerous trials and errors to find the best placements.

(a) (b)

Figure 6. Initial Design of the Wearable Device

In figure 6, image (a) contains the placement of probes on the dorsal side of the arm while image (b) shows the placement of the probes on the palmar side. This is used to help detect the neuromuscular abnormalities and take measurements by attaching disposable EMG patches to the skin of the patient. The circuit of the device is constructed separately from the wearable device to ensure comfort for all users.

3.4 Data Acquisition

This section details the processes of gathering demographics, acquiring EMG data, and processing of data.

3.4.1 Gathering Possible Data Demographics

This study gathered 100 possible demographics randomly. Consent of the respondents was asked to record EMG readings on their hands. All the data gathered is used in the study’s software programming and for the interpretation of the results.

3.4.2 Acquiring EMG Data

The device contains electromyogram sensors used to gather the respondents' EMG data results. The data acquired will then be transferred to a cloud database for storage and processing.

3.4.3 Processing of Data

In this study, the data is segregated, and the participants was categorized according to the following: pregnant, diabetic, overweight, etc. In this procedure, the data that has been collected and stored in the computer during the input stage was processed by implementing machine learning and artificial intelligence algorithms to create a device intended for diagnosing CTS.

3.5 Software Architecture

This section will discuss the software's algorithm selection, model accuracy testing, final accuracy testing, and mobile application development.

3.5.1 Algorithm Selection

This study will utilize an algorithm called a convolutional neural network (CNN) that takes into account the image data file of the EMG data. Afterwards, it is used as an input to work with. Several factors influence performance and inaccuracy rates, including how clean and reliable the data is. Furthermore, there are several approaches to increasing the model's performance (i.e., generalizability). However, each has its own set of advantages and disadvantages, making the technique selection application specific.

CNN architecture differentiates and separates the variables to distinguish dataset categories. A binary classifier works best on RGB representations, where each pixel relates to a specific weight value. The result is then flattened and calculated by multiplying its length, width, and RGB values to obtain the parameters (Velasco, J. S. et al., 2023), as seen below.

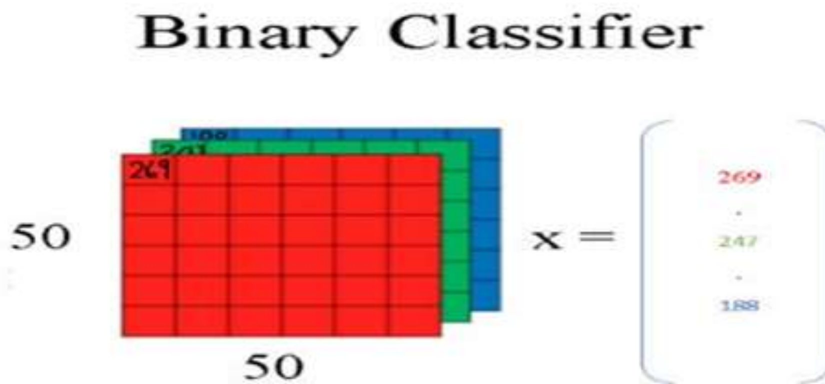


Figure 7. Operation of a binary classifier on RGB values

Furthermore, the study calls for multiple other algorithms to find the best possible fit for our given datasets. Thus, the study will make use of other algorithms, such as the conventional neural networks that were used in our review of related literature.

The researchers implemented a sigmoid activation function in our program, which categorizes predictions into binary outputs. The formula below represents the sigmoid activation function utilized to classify whether the prediction corresponds to a healthy or unhealthy condition.

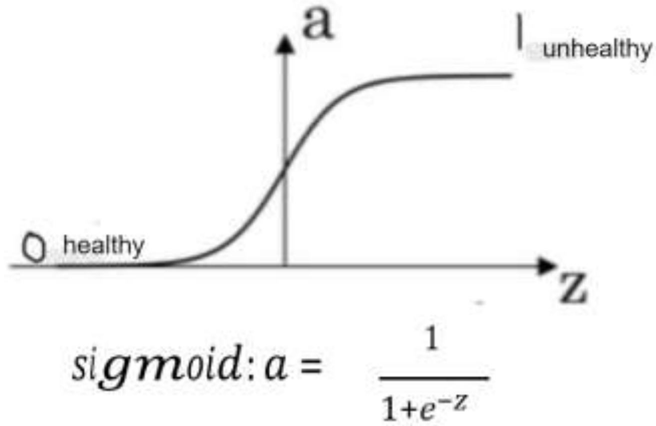


Figure 7.1 Sigmoid Activation Function

The sigmoid activation function is utilized in our program code to introduce non-linearity into the neural network. It maps the input values to a range between 0 and 1, allowing the network to output probabilities for binary classification tasks. By squashing the input values, the sigmoid function helps in modeling and capturing complex patterns in the data, making it a suitable choice for tasks such as sentiment analysis or fraud detection.

3.5.2 Model Accuracy Testing

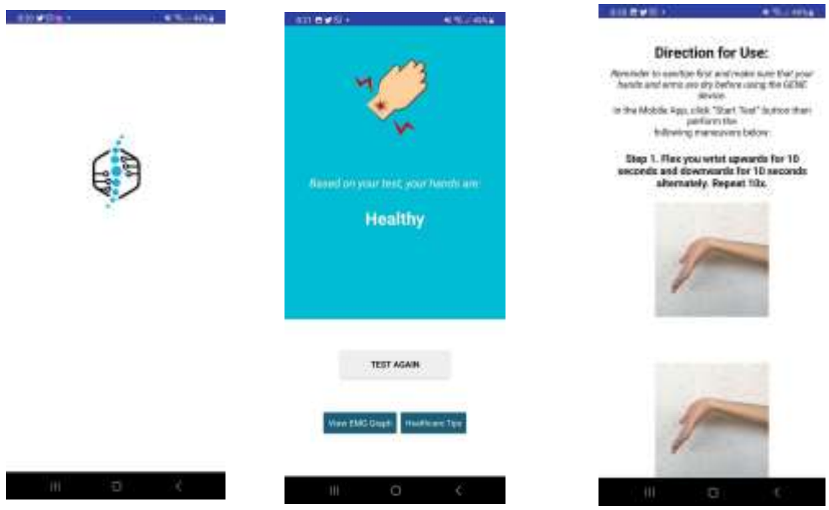
In this part of the study, the researchers will conduct assessments of the accuracy of the models used. They will run the training data from the cross-validation on the model; this will then provide the loss and accuracy results and indicate which epochs to use so as to not overfit the model . The pre-training phase requires at least 5 clinically diagnosed healthy and affected patients with carpal tunnel syndrome. A total of 10 image datasets are gathered. The data is processed and converted into an image data. This dataset is to be gathered around the study's deployment site in Noveleta, Cavite with the approval of local government units.

3.5.3 Final Test of Accuracy

The software was evaluated using the initial datasets. The software's weights was applied after the obtained EMG data, which served as the input, has been processed. The output will show how well the model predicted whether the provided EMG data had symptoms of CTS.

3.5.4 Mobile App Development

The algorithm accurately identified and detected early signs or symptoms of carpal tunnel syndrome using electromyogram (EMG) sensor data. It demonstrates a high degree of sensitivity and specificity in distinguishing between healthy individuals and those with carpal tunnel syndrome. After success in the creation of the algorithm, the connection between the device and a mobile phone is then constructed for applications such as health monitoring. With the model complete, the study calls for a mobile application as a user interface to allow users to access and control the device.



(a) (b) (c)

Figure 8. Initial Interface of Mobile Application

The figure 8, image (a) displays the starting screen, image (b) shows the result of the analysis, and image (c) presents the direction for use. Kodular is used to create the mobile application which offers a glimpse into the user-friendly and visually appealing design, showcasing the intuitive layout, interactive elements, and seamless integration of functionalities aimed at providing an efficient and accessible tool for monitoring Carpal Tunnel Syndrome.

3.6 Project Implementation and Validation

In this part of the study, implementation of the wearable device on the respondents will occur. Subsequently, validation of the results provided by the device will take place.

3.6.1 Validation Accuracy

This procedure of the study will result in the finding of new data demographics that were not part of the initial data acquisition, which can be used for the validation of the software and give an insight on how the program will perform in the real world.

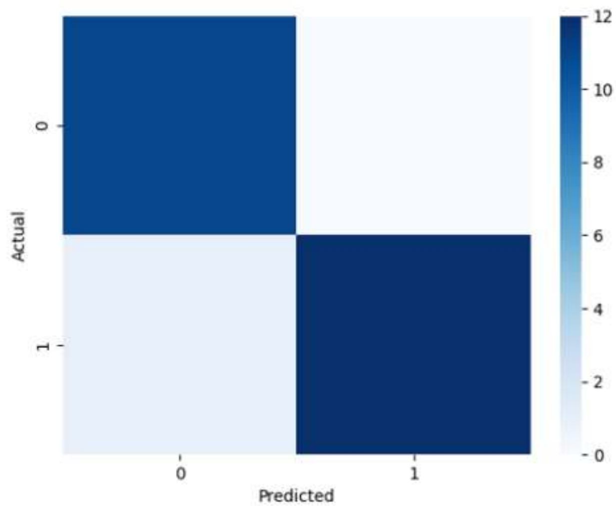


Figure 9. Sample Confusion Matrix

The study used a table of confusion to classify the number of true positive, true negative, false positive, and false negative on the data sets.

3.6.2 Validation from Medical Professionals

The study called for validation for around six medical professionals practicing clinical neurophysiology to check claims of data accuracy and relevance in diagnosing CTS. The medical professionals that were consulted worked in hospitals and clinics around NCR and Region IV-A through zoom calls and scheduled meetings for their assessments and recommendations.

3.7 Statistical Analysis

In this section, there will be a discussion of the statistical analysis that is used for the study.

3.7.1 T-test

To evaluate the effectiveness of the device, the researchers conducted a comprehensive statistical analysis. This analysis involved collecting data from thirty (30) individuals with confirmed carpal tunnel syndrome as well as a control group without the condition. They measured relevant parameters using the GENE device and analyzed the data to identify any significant differences between the two groups.

$$t = \frac{\bar{x} - \mu}{s/\sqrt{n}}$$

Figure 10. T-test formula

The statistical analysis allowed them to assess the overall pattern, trends, and relationships within the data, providing insights into the characteristics and indicators of carpal tunnel syndrome. By conducting this rigorous analysis, they aimed to gain a better understanding of the condition and inform the development and optimization of our device.

Table 9. Questionnaire for Test-Retest Reliability

TEST-RETEST RELIABILITY QUESTIONS	FREQUENCY
• Usability of the app-based monitoring tool	
Excellent	
Good	
Fair	
Poor	
Very Poor	
• Easy navigation and usage of the app-based monitoring tool	
Yes	
No	
• Clarity and logical instructions	
Yes	
No	
• Ability to set-up and use electromyogram sensors with the app-based monitoring tool without difficulty	
Yes	
No	
• Provides useful information about early detetction of Carpal Tunnel Syndrome	
Yes	
No	
• Comfortability using the mobile app and the device	

Yes	
No	
● Technical difficulties encountered while using the app and device	
Yes	
No	
● Possibility to continue using the app and the device	
Very Likely	
Likely	
Unlikely	
Very unlikely	
● Recommendation of the app and monitoring tool for home-based healthcare	
Yes	
No	

3.8 User Acceptance Testing and Feedback Process

The materials that were used for conducting User Acceptance Testing, are survey form created in a virtual environment (in Google Forms), the proponents designed a comprehensive survey using Google Forms that covers relevant aspects of the study including questions about the user's experience with the device as well as the mobile app. The UAT survey forms were validated by the medical professional, specifically Physical Therapist through zoom calls and scheduled meetings for reviewing the UAT survey design and results. After that, the survey form was distributed to 25-30 participants.

Table 10. User Acceptance Testing Questionnaire

	yes	no
Did you find the app-based monitoring tool easy to navigate and use?		
Were the instructions provided clear and easy to follow?		
Were you able to set up and use the electromyogram sensors with the app-based monitoring tool without difficulty?		
Did the app provide useful information about early detection of carpal tunnel syndrome?		
Did you feel comfortable using the app and the device?		
Were there any technical difficulties you encountered while using the app and device?		
How likely are you to continue using the app and the device for monitoring your hand conditions?		
Would you recommend this app and monitoring tool to others for home-based healthcare?		

3.9 Project Work Plan

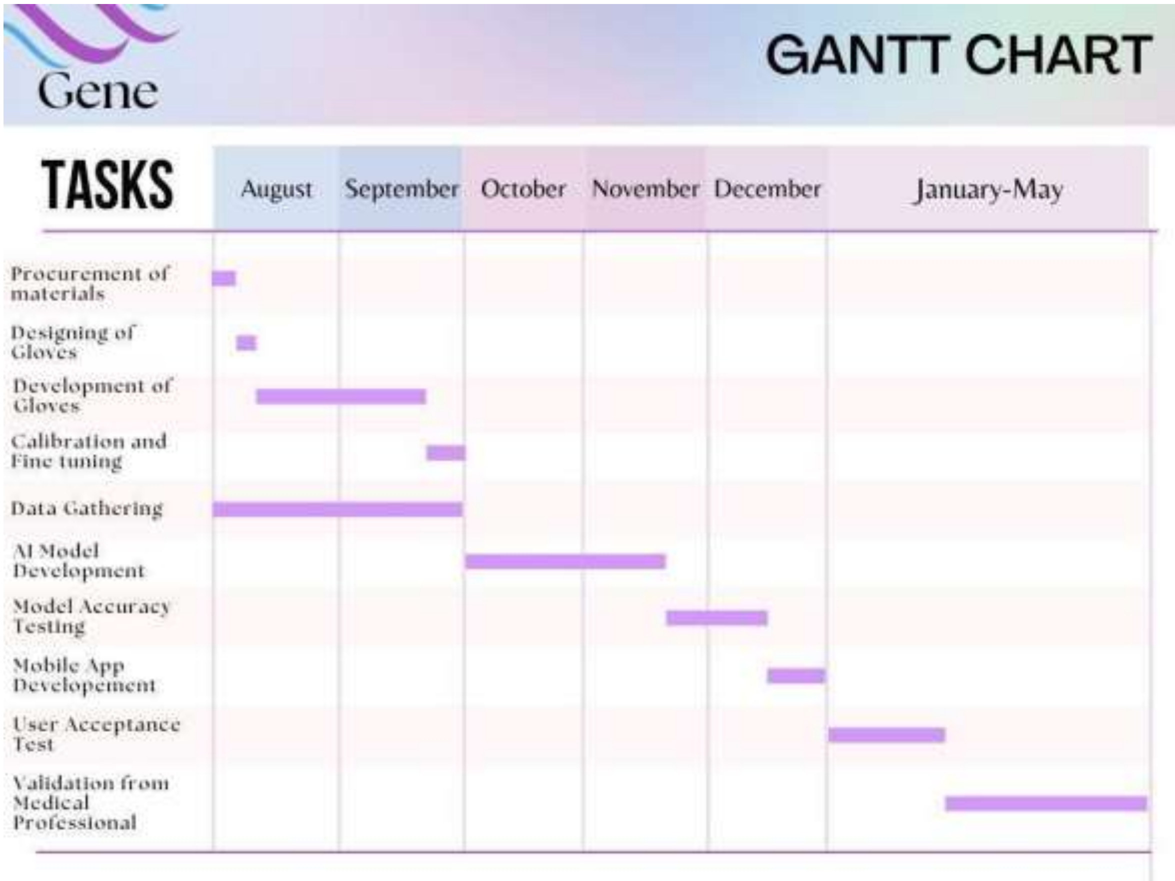


Figure 11. Project Work Plan

The work plan laid out in Figure 11 depicts the project plan for this study. It includes the procurement of materials, the design and development of the necessary hardware, software, and machine learning model, and the device's validation by medical professionals. In two months, the hardware development was finalized, which includes the procurement of the needed materials and equipment as well as the design of the device prototype. Alongside this, several datasets were gathered for the development of the software. This was used to formulate a mathematical model using linear regression, recurrent neural networks, and convolutional neural networks. This also covers the initial construction of the mobile application that will serve as a user interface for the device. Finally, the user acceptance test began on January after the device has been created with the objective of verifying the device's effectiveness, to be validated by medical professionals such as physical therapists. In the defined work plan, there will also be regular consultations and discussions regarding the study with the project adviser, Engr. August C. Thio-ac.

CHAPTER 4

Analysis and Interpretations of Result

This chapter presents the results of the study and its analysis. All findings related to the hardware and software developed for this study, especially the model for machine learning, will be discussed.

4. 1 Project Description

This section of the chapter presents the technical description of the project and a summary of the demographics of 100 respondents.

4.1.1 Project Technical Description

The block diagram of the GENE shows the hardware and software.

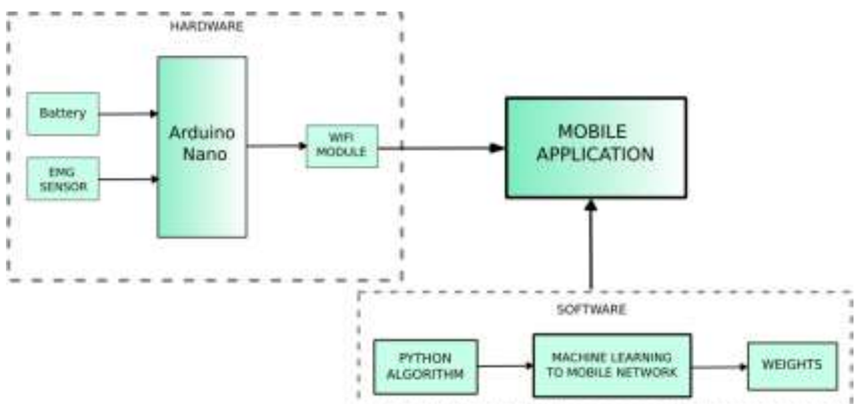


Figure 12. Block Diagram

The device is able to detect the integrity of the median nerve for any strain or wear that may lead to carpal tunnel syndrome, supervised by the developed program.

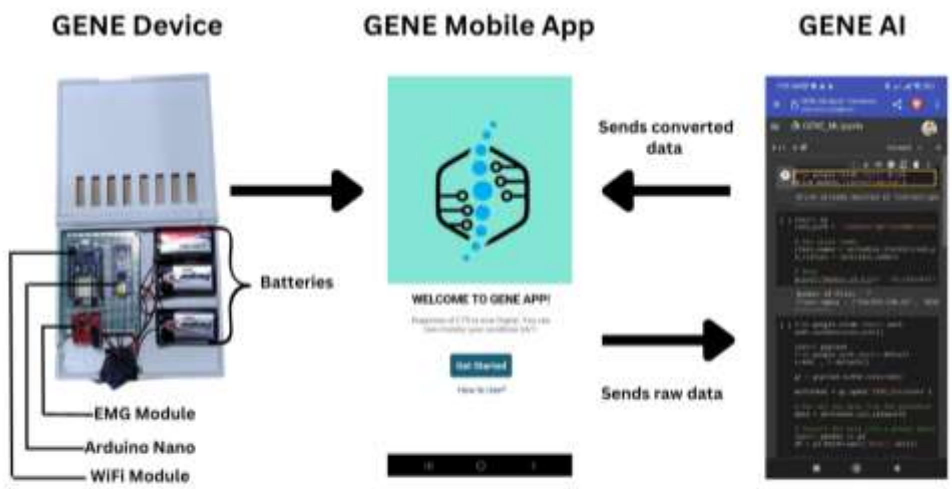


Figure 12.1. Actual Project Flow of Block Diagram

The process in the figure above shows the system that the device follows. Starting from the GENE device, the data is gathered and sent to the GENE mobile application where the GENE AI then processes the raw data and prints out the converted data to be displayed on the mobile application.

4.1.2 Project Data Demographics

The researchers had gathered data using the GENE wearable device from a random sample of 100 respondents. These data sets were used for the accuracy feature of the instrument.

Table 11. Data Demographics from Respondents

DEMOGRAPHIC FACTORS		Frequency	Pecentage
Age	Adolescents (10-17 years)	5	5.00%
	Early Adults (18-34 years)	66	66.00%
	Middle Adults (35-44 years)	16	16.00%
	Late Middle Age (45 and-64 years)	13	13.00%
Gender	Female	45	45.00%
	Male	55	55.00%
BMI	Underweight	37	37.00%
	Healthy	41	41.00%
	Overweight	17	17.00%
	Obese	5	5.00%
	Extremely Obese	0	0%
Pregnant	Yes	2	2.00%
	No	98	98.00%
Underlying Conditions	Yes	47	47%
	Diabetes	2	
	Asthma	3	
	Surgery	2	
	Gout	1	
	High Blood Pressure	5	
	Heart Disease	1	
	Others	33	
	No	53	53%
Diagnosed with CTS	Yes	20	20%
	No	80	80%

Table 11.1. Symptoms of CTS present from Respondents

Symptoms of CTS		Frequency	Percentage
1. Sudden wrist pain	Yes	**24**	**24.00%**
	(Light) 1	12	
	2	3	
	3	0	
	4	1	
	(Severe) 5	8	
	No	**76**	**76.00%**
1.1 How often	(Seldom) 1	14	
	2	2	
	3	0	
	4	5	
	(Always) 5	3	
2. Numbness	Yes	**28**	**28.00%**
	(Light) 1	11	
	2	0	
	3	11	
	4	6	
	(Severe) 5	0	
	No	**72**	**72.00%**
3. Feeling "pins and needles"	Yes	**22**	**22.00%**
	(Seldom) 1	2	
	2	5	
	3	10	
	4	4	
	(always) 5	1	
	No	**78**	**78.00%**
4. Loss of grip strength	Yes	**23**	**23.00%**
	(Seldom) 1	10	
	2	3	
	3	2	
	4	5	
	(always) 5	3	
	No	**77**	**77.00%**
5. Felt night pains	Yes	**22**	**22.00%**
	(Seldom) 1	1	
	2	3	
	3	0	
	4	10	
	5	8	
	No	**78**	**78.00%**
4. Difficulty in Grasping	Yes	**24**	**24.00%**
	(Seldom) 1	3	
	2	11	
	3	1	
	4	4	
	(always) 5	5	
	No	**76**	**76.00%**

While there may be a correlation between age and the likelihood of obtaining CTS, this relationship is not always clear-cut. Although CTS can affect people of any age, older people are more likely to develop it. During the deployment of the study, the most frequent respondents were early adults (66%), followed by middle adults (16%), and late middle-aged adults (13%).

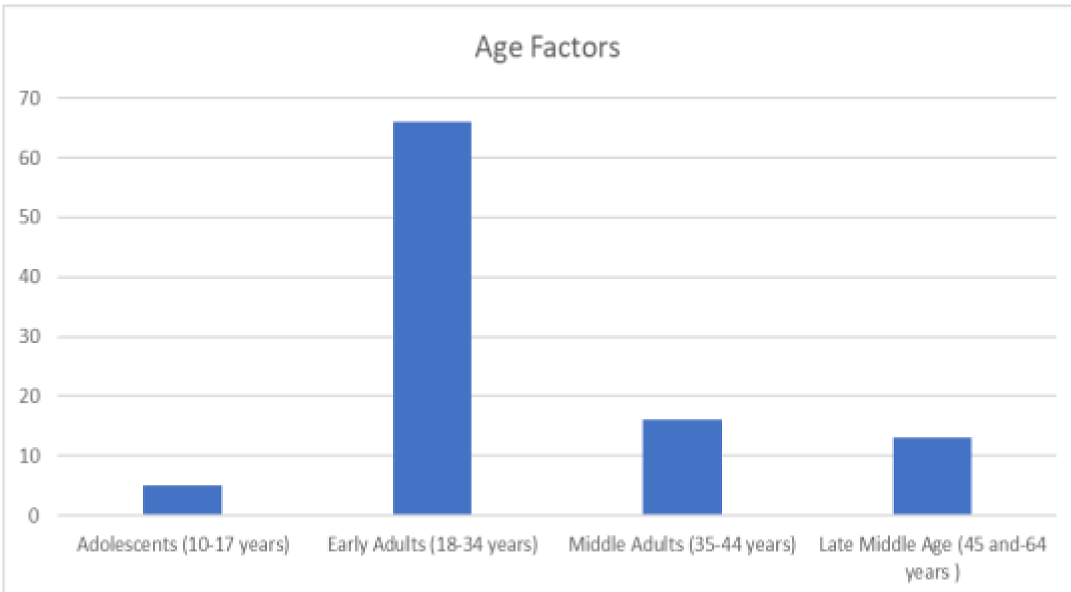


Figure 13. Age Factor Chart

The data have shown that the prevalence of Carpal Tunnel Syndrome tends to increase in age because of things like wrist degeneration and underlying medical disorders. Most symptoms of CTS are seen in people in their 40s to 60s showing 84% from the demographics of late middle-aged respondents. Moreover, throughout the data gathering and deployment, 28% of the 66 respondents from the early adult population showed some symptoms, such as pins and needles as well as numbness.

It is crucial to remember that CTS can, however, also affect people who are younger, particularly those who participate in repetitive hand motions or activities that strain the wrist. Aside from age, however, some professional circumstances and genetic predispositions can affect a person's sensitivity to CTS. Therefore, while age may contribute to the likelihood of developing carpal tunnel syndrome, it is only one of several factors to consider. Furthermore, the gathered data from the 2 unpregnant respondents are healthy yet said to feel often numbness on their hands.

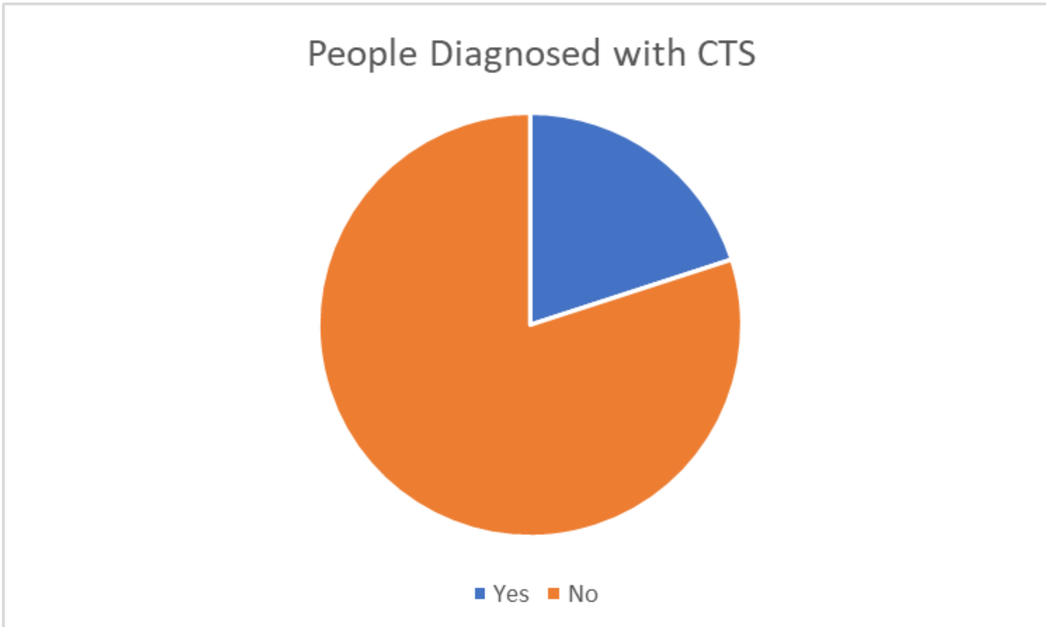


Figure 14. Chart of clinically diagnosed patients with CTS

With the data demographics where 20% are clinically diagnosed and 80% are said to not have CTS, there are still circumstances in which only a few respondents from the latter experienced its symptoms.

4.2 Project Structural Organization

The hardware part of the wearable GENE device is shown in Figure 15.

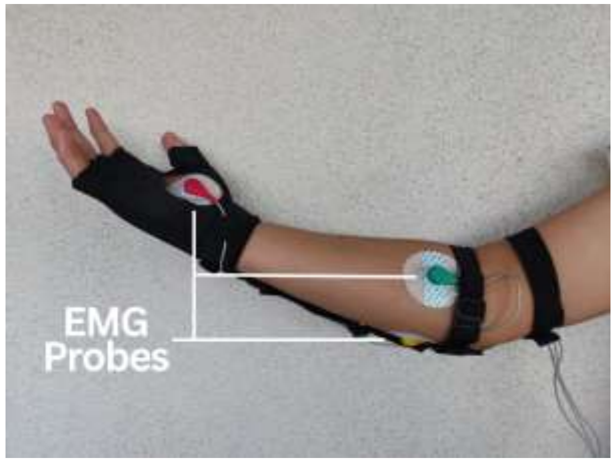


Figure 15. GENE Wearable Device

The wearable device offers user comfort with a sleek, lightweight design. Equipped with advanced sensors, it effortlessly tracks health metrics, and provides accurate prediagnosis of early signs of carpal tunnel syndrome. Careful attention has been given to ergonomic considerations, optimizing the positioning of EMG probes on the patient's palm, forearm, and elbow. The wearable glove, comprising a textile glove, garter straps, slide buckles, and Velcro fasteners, ensures accurate data collection while accommodating diverse hand and arm sizes.

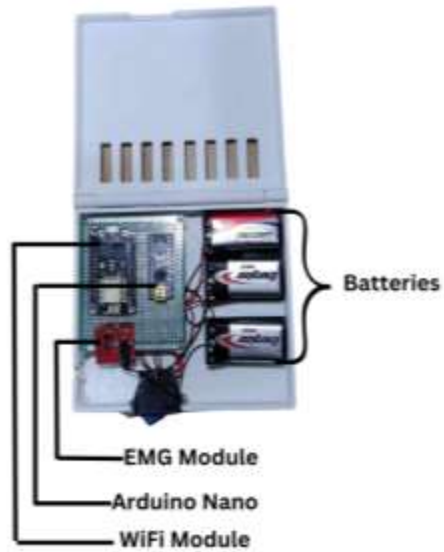


Figure 16. Main Device

The figure shown above is the main device which comprises electronic components that play a crucial role in collecting and transferring data to the mobile application for analysis and interpretation of results. These components consist of an EMG module responsible for capturing data from the EMG sensors, an Arduino Nano, and a Wi-Fi module that enables the wireless transmission of data from the device to the application. The power of the device comes from 3 - 9V batteries, two of which are connected in series to the EMG module. This module sends small electric pulses to the sensors attached to the wearable glove for the acquisition of data.

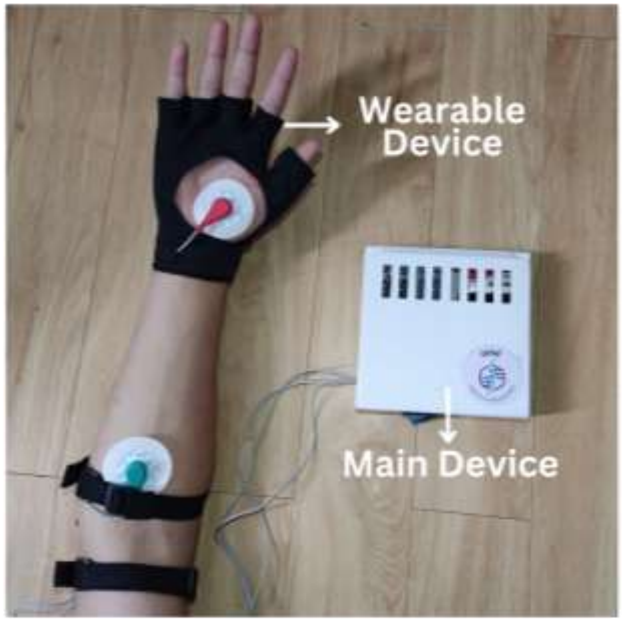
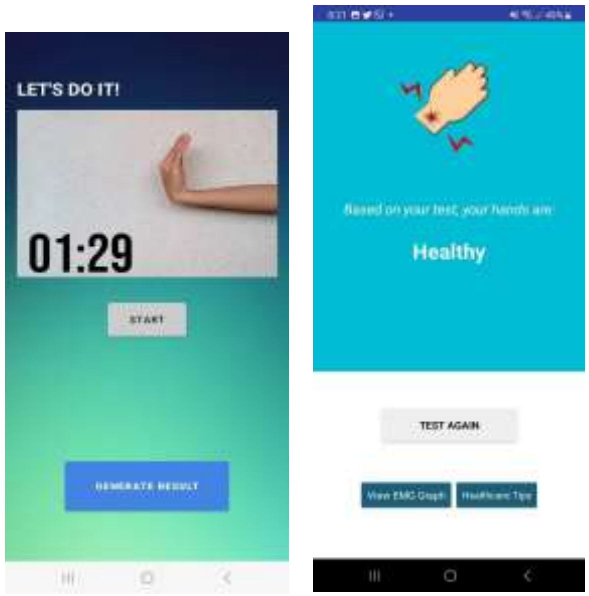


Figure 17. Integration of the main device with the wearable glove

From the figure depicted above, it shows the integration of the hardware gloves and the main device. To ensure the safety and protection of the electronic components, the entire circuit is securely housed within a robust 3D printed case. This enclosure shields the delicate components from potential external factors that could pose a risk of damage or interference to the system. The sturdy construction of the case provides an additional layer of defense, safeguarding the circuitry from physical impacts, dust, moisture, and other potential hazards.

The main interface of the GENE Mobile Application is shown in Figure 18 where the user introduces our mobile application interface, designed to seamlessly connect users with our created device. The interface features a user-friendly design, allowing users to effortlessly pair and establish a secure connection with their device.

With intuitive controls, real-time data visualization, and customizable settings, the application provides a seamless user experience, enabling users to effortlessly interact with and manage their device's functionalities**.**



(a) (b)

Figure 18. Screenshot of GENE Mobile Application Interface

Figure 18 (a) shows the steps to perform the required physical exercises as a guide for users. Upon clicking the "Generate Result" button, as shown on image (b) a diagnosis of whether hands are healthy or not was shown as well as the sample healthy EMG signals for the user's basis of comparison. Additionally, there are buttons for "Test Again" and "See Graph" which will show a pop-up of the user's generated graph from the wearable device.

4.3 Project Capabilities and Limitations

The device is designed to measure nerve integrity, which can also be linked to the early signs of CTS before symptoms become severe; it gathers data on wrist and hand movement patterns, pressure, and force to help diagnose and monitor the progression of the condition; and it provides real-time feedback on wrist electrical signals and movements for the doctor's analysis to make more informed treatment decisions.

While devices such as the GENE offer many benefits, they also come with certain limitations that need to be taken into consideration, such as:

- limited use in a clinical setting as it is primarily a self-monitoring device and may not replace a professional medical evaluation.
- performance of the device can be affected by factors such as hand sizes and muscle composition.
- device is limited only on diagnosing affected median nerves, it may not be able to diagnose other illnesses specifically as of the moment, hence the device was clustered on the healthy, and unhealthy categories; and
- further medical evaluation may be required to confirm the diagnosis.

4.4 User Acceptability Test Result

The results of the user acceptability test indicate unit testing along with end-user testing of the mobile application to ensure the functionality of the study.

Table 12. Frequency table of UAT result

ACTUAL			PREDICTED		
Symptoms of CTS		**Frequency**	**Symptoms of CTS**		**Frequency**
1. Sudden Wrist Pain	Yes	8	1. Sudden Wrist Pain	Yes	7
	No	22		No	23
2. Numbness	Yes	11	2. Numbness	Yes	10
	No	19		No	20
3. Feeling "pins and needles"	Yes	9	3. Feeling "pins and needles"	Yes	8
	No	21		No	22
4. Loss of grip strength	Yes	7	4. Loss of grip strength	Yes	9
	No	23		No	21
5. Felt night pains	Yes	5	5. Felt night pains	Yes	6
	No	25		No	24
6. Difficulty in Grasping	Yes	9	6. Difficulty in Grasping	Yes	12
	No	21		No	18

The results were gathered from thirty (30) respondents who were given the opportunity to interact with the study's software and hardware. The actual part of the table signifies the medically proven respondents that showed signs of carpal tunnel syndrome and healthy respondents. While the predicted part of the table relates to the prediction of the device regarding the user's hand status.

The UAT process involved gathering feedback from users who evaluated our system, and we are pleased to report that the results have been overwhelmingly positive, with users expressing high satisfaction with the system's performance, usability, and overall functionality.

7 out of 8 people who answered Yes to having Sudden Wrist Pain had an output of unhealthy whilst 20 out of 22 people who answered no had an output of healthy.

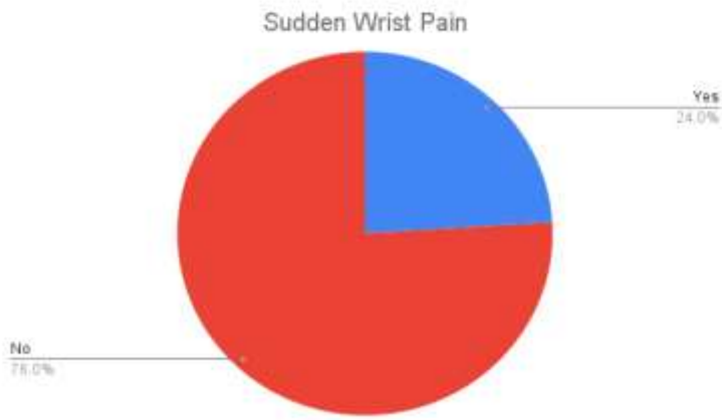


Figure 19. Sudden Wrist Pain

10 out of 11 people who answered Yes to having Numbness had an output of unhealthy whilst 17 out of 19 people who answered no had an output of healthy.

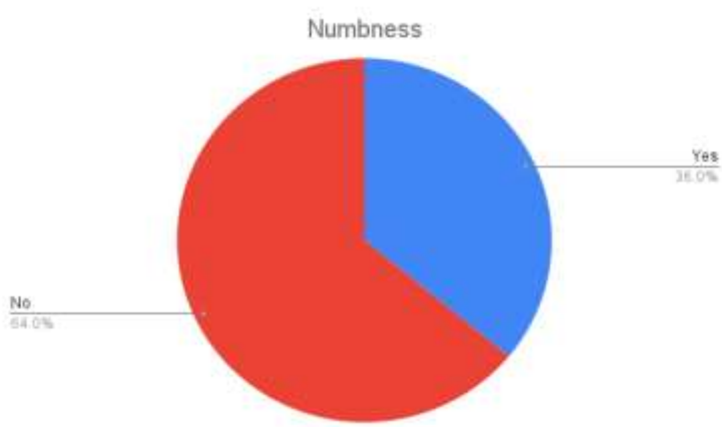


Figure 20. Numbness

7 out of 6 people who answered Yes to having Lost of Grip Strength had an output of unhealthy whilst 21 out of 23 people who answered no had an output of healthy.

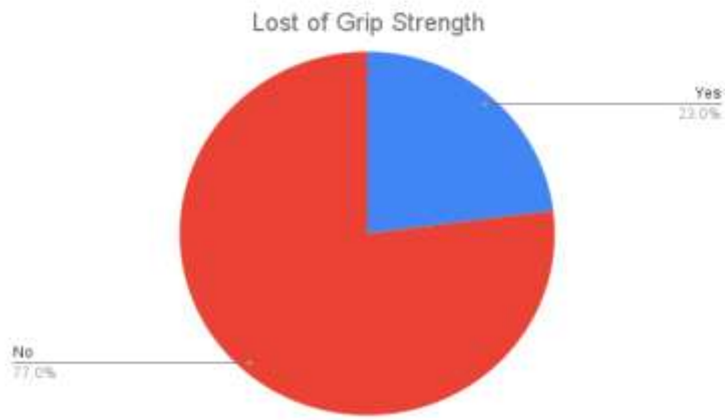


Figure 21. Loss of Grip Strength

8 out of 9 people who answered Yes to having Feeling of "Pins and Needles" had an output of unhealthy19 out of 21 people who answered no had an output of healthy.

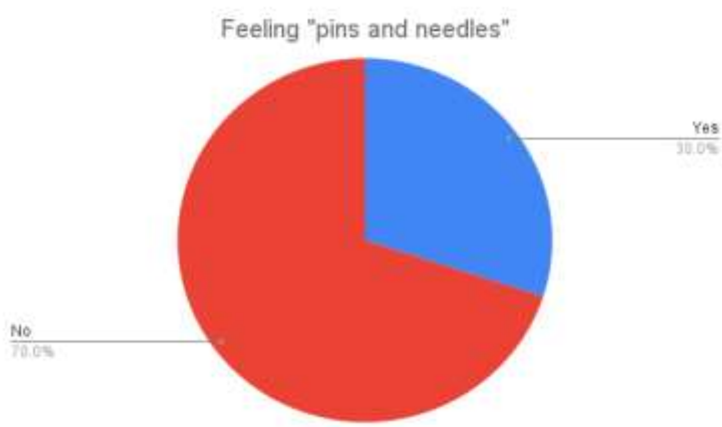


Figure 22. Feeling of "Pins and Needles"

8 out of 9 people who answered Yes to having Difficult in Grasping had an output of unhealthy whilst 19 out of 21 people who answered no had an output of healthy.

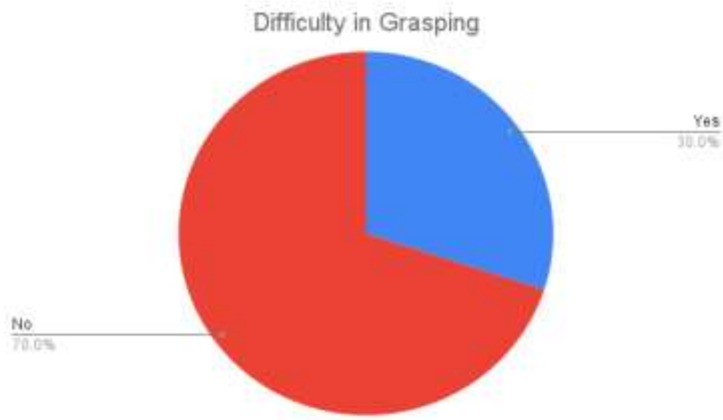


Figure 23. Difficulty in Grasping

5 out of 5 people who answered Yes to having Felt Night pains had an output of unhealthy while 22 out of 25 people who answered no had an output of healthy.

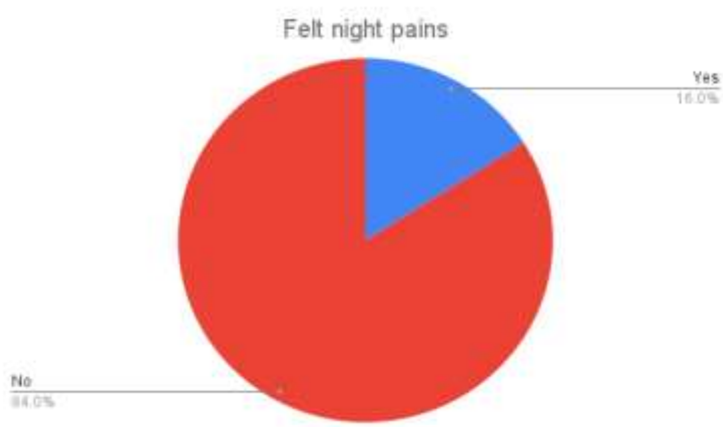


Figure 24. Felt Night Pains

Table 13. Tabulated Results of User Acceptability Test

	yes	no
Did you find the app-based monitoring tool easy to navigate and use?	29	1
Were the instructions provided clear and easy to follow?	29	1
Were you able to set up and use the electromyogram sensors with the app-based monitoring tool without difficulty?	25	5
Did the app provide useful information about early detection of carpal tunnel syndrome?	30	0
Did you feel comfortable using the app and the device?	30	0
Were there any technical difficulties you encountered while using the app and device?	18	12
How likely are you to continue using the app and the device for monitoring your hand conditions?	15	15
Would you recommend this app and monitoring tool to others for home-based healthcare?	30	0

Based on the results of the user acceptability test, the device received overwhelmingly positive sentiments, indicating its exceptional quality. Users expressed high levels of satisfaction and approval with the device, highlighting its effectiveness, functionality, and overall performance. The positive feedback from the testing phase serves as a strong indicator that the device is effective and meets user expectations.

4.4.1 Test-Retest Reliability

The researchers aimed to assess the test-retest reliability and accuracy of the device. Questionnaires, guided by medical professionals, were also used to further assess the gathered respondents. The device tested a total of 30 new respondents. And have conducted a manual testing to manually input the devices accuracy and had correctly predicted 27 out of the 30 respondents The researchers assessed that the average accuracy is around 90% when compared to the industry standards, which is DASH, which was calculated to 89%, which is slightly better depending on the current datasets**.**

4.5 Results

A healthy or unhealthy dataset would then be the input that needs to be calculated using a sigmoid activation function if the given data had more values on the same pixel. This function then yields a value; if the value was closer to 0, the output would be healthy, and if the value was closer to 1, the output would be unhealthy. The system generated a validation accuracy rating of 87%, and VGG 16 displayed the best accuracy and validation accuracy results. Beginning with an accuracy of less than 70%, we even went as low as 50%. The datasets we gave were insufficient, which is why we were able to enhance our accuracy to 100% and our validation accuracy to roughly 87% after doing further data collection from our deployment site. Following the initial validation accuracy of around 60–70%, with the addition of data sets used on the algorithm, the produced validation accuracy increased up to 87%. With that, the researchers created a manual program to check the accuracy of the output of 87%. and tested it on new data. This new data was validated alongside a medical professional and is not used in the training of said model. With that, the model had successfully predicted 8 out of 10 of these new data sets. The researchers believe that with more data, it could have an output of around 90% and above.

Table 14. Model Accuracy

VGG16	87%
RESNET	85.71%
XCEPTION	71.43%
VGG199	68.29%
INCEPTION	57.14%

4.5.1 Statistical Metrics of Machine Learning Training

In this part, two important statistical variables, F1 score and accuracy, were used to assess how well machine learning models performed in terms of [what capacity?]. These metrics offer a full evaluation of the model's capacity for outcome classification and prediction, allowing for a thorough examination of its training efficiency.

	precision	recall	f1-score	support
Healthy	0.50	1.00	0.67	3
Unhealthy	0.00	0.00	0.00	3
accuracy			0.50	6
macro avg	0.25	0.50	0.33	6
weighted avg	0.25	0.50	0.33	6

Figure 25. Statistical Metrics of machine learning training

4.5.2 Confusion Matrix

This matrix offers helpful insights on the model's capacity to accurately classify cases and spot potential errors by providing a thorough breakdown of true positive, true negative, false positive, and false negative predictions. Different architectures were run to assess the accuracy of the model.

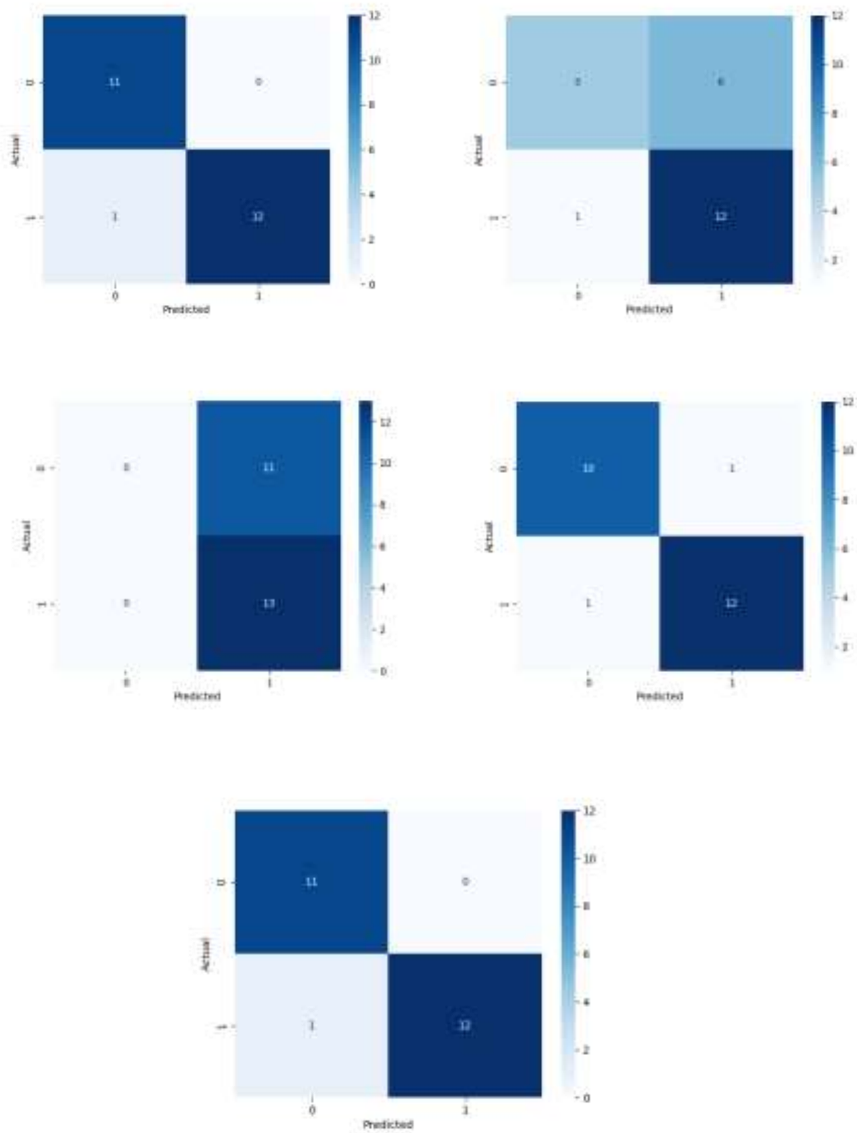


Figure 26. Results of various Confusion Matrixes

(VGG16, VGG19, Resnet50, XCeption, InceptionV3)

Among the various models evaluated, it was found that the VGG16 model exhibited the highest accuracy rating when compared to VGG19, ResNet50, XCeption, and InceptionV3. Extensive testing and validation revealed that the VGG16 model consistently outperformed the other models in terms of accurately classifying and recognizing the underlying features in the dataset. Its deep architecture and extensive convolutional layers enabled it to capture intricate details and nuances, leading to superior performance. The VGG16 model's high accuracy rating highlights its effectiveness as a powerful tool for image recognition and classification tasks, making it a preferred choice in applications where precise and reliable results are of utmost importance.

4.5.3 Validation of results

From a population of thirty (30) respondents, the validation accuracy of the device was identified to form the confusion matrix shown below. True positives result in 15 out of 30 figures, and true negatives result in 11 out of 30 true negatives. Moreover, 4 out of 30 yields a false positive, and 0 out of 30 yields a false negative.

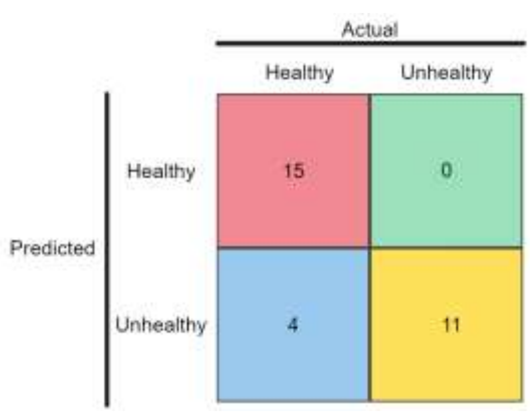


Figure 27. Confusion Matrix of Result Validation

4.6 Discussion and Interpretation of Findings

The implementation of the proposed system involves the development of an app-based monitoring tool that connects to the EMG sensors and provides real-time monitoring and analysis. The app collects the EMG data from the sensors and preprocesses it using digital signal processing techniques. The preprocessed data is then fed into the trained machine learning model for classification.

To ensure usability and user-friendliness, the app provides an intuitive interface for users to monitor their EMG signals, view real-time visualizations, and receive alerts if the system detects patterns indicative of CTS. To evaluate the effectiveness of the proposed system, a comprehensive evaluation is conducted. A dataset consisting of EMG signals from a diverse group of individuals, including both healthy individuals and those diagnosed with CTS, is collected. The dataset is used for training and testing supervised machine learning models.

4.7 Results and Discussion

The results of the evaluation demonstrate the effectiveness of the proposed system for the early detection of CTS. The supervised machine learning models achieve high accuracy in classifying EMG signals as either indicative of CTS or not. The sensitivity and specificity of the models indicate their ability to correctly identify individuals with CTS and distinguish them from healthy individuals. The app-based monitoring tool provides a user-friendly interface that allows individuals to monitor their muscle activity and receive timely notifications if abnormal patterns are detected. This empowers users to take proactive measures, such as modifying their activities or seeking medical attention, in the early stages of CTS with an acceptable accuracy that is on par with the standards stated above.

Upon conducting user acceptance testing (UAT), the researchers found that the use of the device offers a promising approach for the early detection of carpal tunnel syndrome by having been able to see promising outputs as seen from the figures 16 to 22. By analyzing the gathered data from EMG, the machine learning model exhibits a high level of accuracy in detecting early signs of CTS. Users expressed confidence in the system's ability to identify potential hand problems, enabling them to seek appropriate medical professionals for immediate treatment. The use of Google Forms as a tool for conducting the UAT proved effective in gathering feedback from participants. There are also several suggestions for improving the app and device. Users suggest improving the design of the gloves; they should be able to be worn easily without experiencing discomfort or hindrance in performing daily activities. Aside from that, they also suggest continuously improving the user interface of the monitoring app to ensure simplicity and ease of use.

4.7.1 Statistical Test

An independent samples t-test is employed as this study's statistical test. This was done by using results from the user acceptability test and then comparing the measurements obtained from individuals with confirmed carpal tunnel syndrome to a control group without the condition. By analyzing the data collected using our device, it was determined that there were statistically significant differences between the two groups in terms of the measured parameters. The t-test allowed us to quantitatively assess the significance of these differences and evaluate the diagnostic efficacy of our device. The results of the t-test provided valuable information about the ability of our device to accurately identify individuals with carpal tunnel syndrome based on the measured parameters. Through this statistical test, the effectiveness of the device is shown to display its potential for early detection of carpal tunnel syndrome.

Table 15. Statistical test Results

	Predicted Positive	Predicted Negative
Actual Positive	15	0
Actual Negative	4	1

CHAPTER 5

Summary, Conclusions, and Recommendations

In this chapter, the researchers present the findings and analysis derived from the study. The primary objective of this research was to develop a device for early detection of carpal tunnel syndrome and investigate its effectiveness. By discussing these findings and subjecting them to critical analysis, the researchers aim to address all research objectives stated at the beginning of this study. In turn, it is hoped that these insights may contribute to a broader understanding of early detection of carpal tunnel syndrome using electromyogram sensors with an app-based monitoring tool and applications of supervised machine learning models for home-based healthcare.

5.1 Summary of findings

1. The study achieved successful development of a microcontroller-based glove, which revolutionizes the gathering of electrical activity along the median nerves. This innovative glove incorporates electromyogram (EMG) probes and leverages advanced microcontroller technology to provide optimal probe placement and angle of the hands. Through extensive research and testing, the study determined the ideal locations for the EMG probes, ensuring accurate and reliable measurements of the electrical activity. Additionally, by determining the optimal angle of the hands, the glove maximizes the efficiency of data collection. This groundbreaking advancement opens new possibilities for precise and non-invasive

assessment of median nerve function, offering potential applications in diagnostics, rehabilitation, and personalized treatment strategies.

2. The study successfully formulated a mathematical model using Convolutional Neural Networks (CNN) to differentiate between healthy individuals and those affected by a certain condition. By training the CNN on a large dataset of relevant medical data, the model was able to learn complex patterns and features indicative of health or an affected status. The study then integrated this model into a mobile application, allowing for convenient and real-time evaluation of patients' health. Users can simply input their data, and the CNN-based algorithm quickly analyzes and classifies their health status. This breakthrough provides a user-friendly tool for early detection, monitoring, and personalized care, empowering individuals to take control of their well-being conveniently through their mobile devices.

3. The study accomplished the successful development of machine learning-based application software that serves as an effective monitoring tool for the device. By leveraging advanced machine learning algorithms, the application is capable of analyzing and interpreting the data collected by the device in real-time. This software not only provides valuable insights and visualizations of the data but also employs machine learning techniques to detect patterns, trends, and anomalies. Through continuous monitoring, users can gain a comprehensive understanding of their health status and make informed decisions about their well-being. The machine-learning-based application software adds a layer of

intelligence and convenience to the device, enhancing its functionality as a reliable and insightful monitoring tool.

4. The study successfully conducted a user acceptability test to verify the effectiveness of the newly created device. Participants in the test expressed high levels of satisfaction, with approximately 83% of them acknowledging the device's effectiveness in addressing their needs. Moreover, 87% of the participants reported improved outcomes compared to their previous methods, highlighting the successful integration of the device into their daily routines. These findings validate the utility and usability of the device, affirming its acceptance and potential for widespread use among users.

5. In close collaboration with a medical professional, the study successfully implemented and validated the newly developed device. The expertise and insights provided by the medical professional played a vital role in ensuring the device's accuracy and reliability. Through a rigorous evaluation process, the device demonstrated consistent and accurate results, aligning closely with the medical professional's assessments. This collaboration not only reinforced the device's effectiveness but also instilled confidence in its performance among the medical community. The successful implementation and validation of the device in partnership with a medical professional have paved the way for its potential integration into clinical settings, promising improved diagnostics and patient care.

5.2 Conclusion

1. The research team has successfully developed a microcontroller-based glove that incorporates electromyogram (EMG) sensors. These sensors are strategically placed on the palm, Elbow, and forearm to capture the electrical activity along the median nerves. By identifying the optimal placements of the EMG probes and considering the optimal hand angles, the glove ensures accurate and reliable data collection of neuromuscular activity. This innovation enables precise monitoring and assessment of the electrical signals in the hand, specifically targeting the detection of carpal tunnel syndrome.

2. A mathematical model has been formulated using Convolutional Neural Networks (CNN) to differentiate between healthy individuals and those affected by carpal tunnel syndrome. The model takes into account the data collected by the EMG sensors on the glove. By analyzing the wave fluctuations of the electrical signals, the CNN model effectively determines the presence of any neuromuscular abnormalities. The outcomes of the model was integrated into a mobile application, providing users with real-time information regarding their nerve integrity status.

3. The research team has developed a machine learning-based application software that functions as a monitoring tool for the wearable device. This software is designed to work seamlessly with the microcontroller-based glove, receiving and analyzing the data captured by the EMG sensors. Through the integration of advanced algorithms, the software provides users with valuable insights into their nerve integrity and helps in early detection

of carpal tunnel syndrome. The application serves as a user-friendly interface, allowing individuals to track their neuromuscular health conveniently.

4. A user acceptability test has been conducted to assess the effectiveness of the developed device. The test involved a group of respondents using the microcontroller-based glove and monitoring the results produced by the machine learning model. The outcomes of the test demonstrated that the device successfully predicted the nerve integrity status of the users. The majority of respondents reported satisfaction with the device's performance and found it to be a reliable tool for early detection of carpal tunnel syndrome. These positive results validate the device's effectiveness and its potential for widespread use.

5. In collaboration with a medical professional, the developed device has been implemented and validated. The medical professional assessed the device's performance and accuracy by comparing its predictions with the results of clinical examinations and diagnoses. The device exhibited a high level of accuracy, correctly predicting the nerve integrity status of 8 out of 10 respondents. The collaboration with the medical professional ensures that the device meets the necessary standards and provides reliable information for medical practitioners, reinforcing its credibility in the field of carpal tunnel syndrome detection and monitoring.

5.3 Recommendations

1. Enhance the mobile application to track symptoms, display battery indicators, and receive personalized recommendations for preventing and managing CTS.

2. Collect a larger dataset of EMG signals from individuals with different stages and severities of CTS to expand the capabilities of the developed system. Incorporating regular follow-up evaluations and user feedback to continuously improve the system's effectiveness and address any emerging issues.

3. Design models to handle the variability in EMG signals across different individuals, account for potential confounding factors, and adapt to individual-specific patterns over time. As well as developing a comprehensive follow-up strategy for individuals diagnosed with CTS or at risk of developing it, including features for continuous monitoring of muscle activity and symptom progression over time.

4. Explore advanced classification algorithms to improve the accuracy and reliability of the models as to provide personalized recommendations for preventive measures, exercise programs, and ergonomic adjustments based on the individual's specific condition and needs.

5. Conduct validation studies and clinical trials involving a diverse group of participants to establish the effectiveness and reliability of the proposed system for early detection of CTS.

References

Ablove, T., Ablove, R. H., and Ablove, T. S. "Prevalence of carpal tunnel syndrome in pregnant women WISCONSIN MEDICAL JOURNAL WISCONSIN MEDICAL JOURNAL prevalence of Carpal tunnel Syndrome in pregnant Women," Wisconsin Medical Journal, vol. 108, no. 4, 2009. [Online]. Available: https://www.researchgate.net/publication/26811776.

Aljamali, N., Najim, M., and Alabbasy, A. "Types of Electrical Insulators and their Electrical Applications," 2021, vol. 6, pp. 18-23.

[Aljure, J., Eltorai, I., Bradley, W. E., Lin, J. E., and Johnson, B. "Carpal tunnel syndrome in paraplegic patients," Paraplegia, vol. 23, no. 3, pp. 182-186, 1985. doi: 10.1038/sc.1985.31

Ayrapetyan, M., Miao, W., and Rourke, K. O. "Over-Use Warning Glove for Carpal Tunnel Syndrome," pp. 1-17, 2021.

Bekele, A., Abebe, G., Hailu, T., Fekadu, T., Gebremickael, A., Getachew, T., Churko, C., Alelign, D., Wassihun, B., Teshome, D., and Bukala, Z. "Prevalence and Associated Factors of Carpal Tunnel Syndrome Among Diabetic Patients in

Arba Minch General Hospital, South West Ethiopia, 2021," Diabetes, Metabolic Syndrome and Obesity: Targets and Therapy, vol. 15, pp. 983-993, 2022. doi: 10.2147/DMSO.S356484

Blumenthal, S., Herskovitz, S., and Verghese, J. "Carpal tunnel syndrome in older adults."

Clinic, C. "Overuse syndrome: Symptoms, treatment & prevention," Cleveland Clinic. [Online]. Available: https://my.clevelandclinic.org/health/diseases/4706-overuse-syndrome-of-the-hands-and-arms. [Accessed: Jun. 9, 2022].

Durkan, J. A. "A new diagnostic test for carpal tunnel syndrome," This is an enhanced PDF from The Journal of Bone and Joint Surgery, vol. 73, 1991. [Online]. Available: www.jbjs.org.

El Miedany, Y., El Gaafary, M., Youssef, S., Ahmed, I., and Nasr, A. "Ultrasound assessment of the median nerve: a biomarker that can help in setting a treat to target approach tailored for carpal tunnel syndrome patients," SpringerPlus, vol. 4, no. 1, pp. 1-10, 2015. doi: 10.1186/s40064-014-0779-4

Gellman, H., Chandler, D. R., Petrasek, J., Sie, I., Adkins, R., and Waters, R. L. "Carpal tunnel syndrome in paraplegic patients," Journal of Bone and Joint Surgery - Series A, vol. 70, no. 4, pp. 517-519, 1988. doi: 10.2106/00004623-198870040-00006

Goto, S., Mahara, K., Beussink-Nelson, L., Ikura, H., Katsumata, Y., Endo, J., Gaggin, H. K., Shah, S. J., Itabashi, Y., MacRae, C. A., and Deo, R. C. "Artificial intelligence-enabled fully automated detection of cardiac amyloidosis using electrocardiograms and echocardiograms," Nature Communications, vol. 12, no. 1, 2021. doi: 10.1038/s41467-021-22877-8

Huntley, D. E. and Shannon, S. A. "Carpal tunnel syndrome: a review of the literature," Dental Hygiene, vol. 62, no. 7, pp. 316-320, 1988. doi: 10.7759/cureus.7333

Hussien, A., Youssef, S., and Fathy, C. "Tracking of Medical Muscular Activities for Identification of Human Motor Disability using Biomedical, Electromyogram Emg Signals," 2016, pp. 80-83.

Ilbay, K., Übeyli, D., Ilbay, G., and Budak, F. "A New Application of Recurrent Neural Networks for EMG-Based Diagnosis of Carpal Tunnel Syndrome," 2018.

Kiranyaz, S., Ince, T., Abdeljaber, O., Avci, O., and Gabbouj, M. "1-D Convolutional Neural Networks for Signal Processing Applications," in ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings, 2019, pp. 8360-8364. doi: 10.1109/ICASSP.2019.868219

Koyama, T., Sato, S., Toriumi, M., Watanabe, T., Nimura, A., Okawa, A., Sugiura, Y., and Fujita, K. "A screening method using anomaly detection on a smartphone for patients with carpal tunnel syndrome: Diagnostic case-control study," JMIR MHealth and UHealth, vol. 9, no. 3, pp. 1-10, 2021. doi: 10.2196/26320

Kruger, V. L., Krafr, G. H., Deitz, J. C., Ameis, A., and Polissar, L. "Carpal Tunnel Syndrome: Objective Measures and Splint Use," 1991.

Leffler, C. T., Gozani, S. N., Nguyen, Z. Q., and Cros, D. "An automated electrodiagnostic technique for detection of carpal tunnel syndrome," Neurology and Clinical Neurophysiology, vol. 2000, no. 3, pp. 2-9, 2000. doi: 10.1162/15268740052050988

Leung, D. "Carpal Tunnel Syndrome," Encyclopedia of the Neurological Sciences, vol. 77, pp. 602-605, 2014. doi: 10.1016/B978-0-12-385157-4.00652-7

MacK, M. and Min, C. H. "Design of a Wearable Carpal Tunnel Syndrome Monitoring Device," in Midwest Symposium on Circuits and Systems, 2019, pp. 1195-1198. doi: 10.1109/MWSCAS.2019.8884804

Phillips, L. H. and Juel, V. C. "The role of electrodiagnostic testing in carpal tunnel syndrome," Neurosurgical Focus, vol. 3, no. 1, p. E4, 2008. doi: 10.3171/foc.1997.3.1.5

Piper, B. "Design and Validation of a Smart Brace; Wearable Technology for Carpal Tunnel Syndrome," 2017. [Online]. Available: http://atrium.lib.uoguelph.ca/xmlui/handle/10214/11940.

Shiri, R. and Falah-Hassani, K. "Computer use and carpal tunnel syndrome: A meta-analysis," Journal of the Neurological Sciences, vol. 349, no. 1-2, pp. 15-19, 2015. doi: 10.1016/j.jns.2014.12.037

Singh, A., Hazarika, A., Talukdar, C., Bhuyan, M., Dutta, L., Barthakur, M., and Chakraborty, K. "Microcontroller-Based Online Nerve Parameter Estimation for Diagnosis of Healthy Subject Using Real-Time Nerve Conduction Study Signal Acquired Using Voltage Controlled Neurostimulator," IEEE Transactions on Industrial Informatics, vol. 17, no. 11, pp. 7546-7553, 2021. doi: 10.1109/TII.2021.3050471

Swen, W. A. A., Jacobs, J. W. G., Bussemaker, F. E. A. M., De Waard, J. W. D., and Bijlsma, J. W. J. "Carpal tunnel sonography by the rheumatologist versus nerve conduction study by the neurologist," Journal of Rheumatology, vol. 28, no. 1, pp. 62-69, 2001.

Theses, M. and Svendsen, P. "University of New Hampshire Scholars' Repository Development of Electronic Testing Devices That Detect Peripheral Neuropathies," University of New Hampshire, 2018.

Tsamis, K. I., Kontogiannis, P., Gourgiotis, I., Ntabos, S., Sarmas, I., and Manis, G. "Automatic electrodiagnosis of carpal tunnel syndrome using machine learning," Bioengineering, vol. 8, no. 11, pp. 1-15, 2021. doi: 10.3390/bioengineering8110181

Velasco, J. S. et al. "Image classifier differentiating tumour from healthy MRI scans using ...," arpnjournals, 2023. [Online]. Available: http://www.arpnjournals.org/jeas/research_papers/rp_2023/jeas_0723_1082.pdf .

Yan, Y., Fan, H., Li, Y., Hoeglinger, E., Barr, A., O'connell, G. D., and Harris-Adamson, C. "Applying wearable technology and a deep learning model to predict occupational physical activities," Applied Sciences, vol. 11, no. 20, 2021. doi: 10.3390/app1120963

ANNEX I

BILL OF MATERIALS

Table 16. Bill of Materials

Item No.	Item Description	Quantity	Unit Cost	Total
1.	NodeMCU ESP8266	3	150	450
2.	AD8266 EMG Sensor	3	1200	3600
3.	Arduino Nano	3	289	867
4.	Wire	-	20	20
5.	PCB Board	3	180	540
6.	3D Printer Filament	1	765	765
7.	Switch Button	3	44	132
8.	Gloves	3 pairs	150 each	450
9.	Garter	1 roll	140	140

ANNEX II

Early Detection of Carpal Tunnel Syndrome using Electromyogram with an App Based Monitoring Tool and Applications of Supervised Machine Learning Model for Home-based Healthcare

ASSESSMENT FORM

A. Personal Information

1. Name

____

2. Age

____

3. Gender

☐ Male
☐ Female

4. Address

____

5. Contact Number

____

B. Hand Condition and Other Information

1. State your BMI

____

2. Are you currently pregnant or have been recently pregnant the past few mo ☐ ?

   Yes

   ☐ No

3. Do you have any underlying conditions? (ex: diabetes, asthma, anemia, etc.)

   ☐ Yes

   ☐ No

   If yes please specify:

4. Are you clinically diagnosed with Carpal Tunnel Syndrome?

   ☐ Yes

   ☐

No

5. Do you feel pain around the median palm region? (Thumb, Index, Middle finger)

   ☐ Yes

   ☐ No

   If yes, please rate the pain from 0-10 (Kung oo, i-rate ito mula 0-10)

	0	1	2	3	4	5	6	7	8	9	10	
No Pain	○	○	○	○	○	○	○	○	○	○	○	Worst Pain Possible

   How often do you feel the pain?

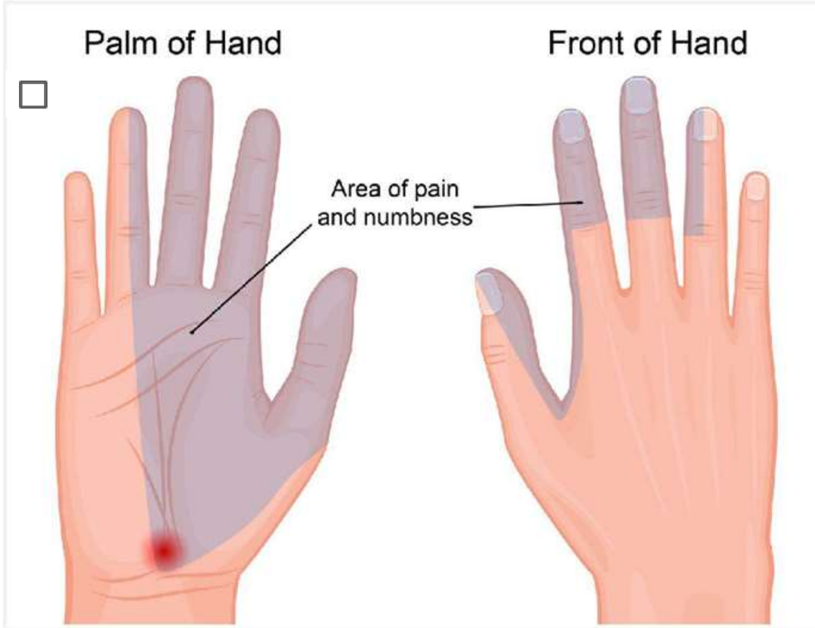
	1	2	3	4	5	
seldom	○	○	○	○	○	always

6. When using your hands for a long period of time, do you feel any numbness? (Nakakaramdam ka ba ng pamamanhid sa iyong kamay matapos itong gamitin?)

   ☐ Yes

   ☐ No

If yes, please specify which part of the hand feels numb? (Kung oo, piliin kung saang parte ng kamay mo ito nararanasan.) Note: Check all possible answers.



☐ Thumb (Hinlalaki)

☐ Index Finger (Hintuturo)

☐ Middle Finger (Hinlalato)

☐ Ring Finger (Palasingsingan)

☐ Pinkie Finger (Hinliliit)

Please rate the numbness from 0%-100%. (Paki-rate ang pamamanhid mula 0%-100%.)

___

7. Does your hand suddenly feel 'pins and needles' even without it being weighed down? (Nakakaramdam ka ba ng pangingimay sa iyong kamay kahit na hindi ito nadaganan/nadadaganan?)

   ☐ Yes

   ☐ No

   If yes, please state how often. (Kung oo, pakisabi kung gaano kadalas.)

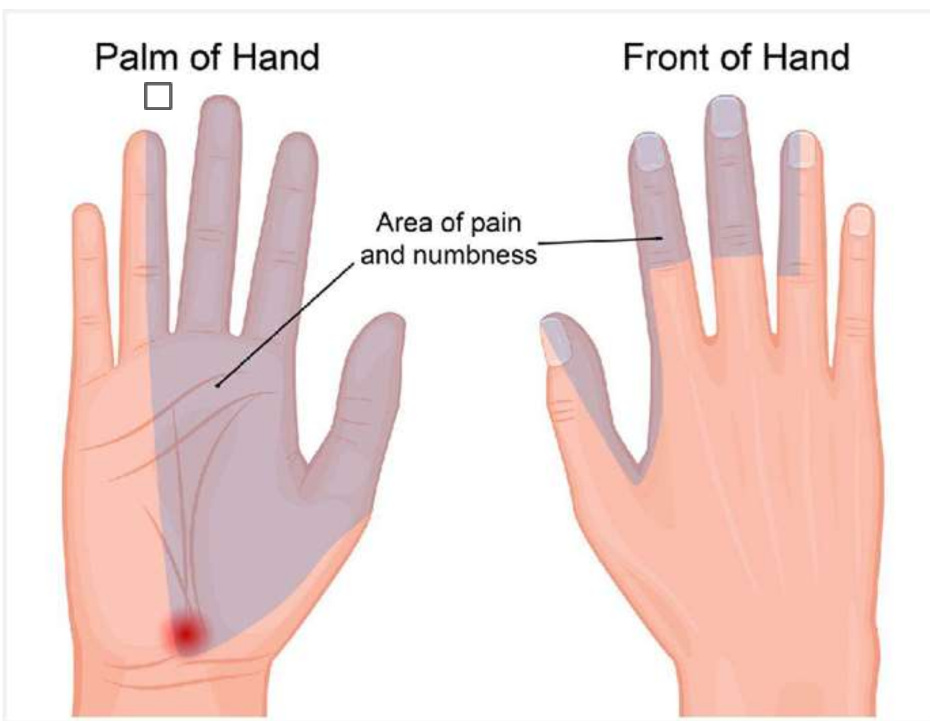
	1	2	3	4	5	
seldom	○	○	○	○	○	always

8. Do you feel loss of grip strength in your hand? (Nararamdaman mo ba ang pagkawala ng lakas ng pagkakahawak sa iyong kamay?)

   ☐ Yes

   ☐ No

   If yes, please specify which part of the hand. (Kung oo, piliin kung saang parte ng kamay mo ito nararanasan.)



Thumb (Hinlalaki)

☐ Index Finger (Hintuturo)

☐ Middle Finger (Hinlalato)

☐ Ring Finger (Palasingsingan)

☐ Pinkie Finger (Hinliliit)

If yes, please state how often. (Kung oo, pakisabi kung gaano kadalas.)

	1	2	3	4	5	
☐ ldom	○	○	○	○	○	always

9. Do you feel night pains or sudden pain in your hands at night? (Nakakaramdam ka ba ng biglaang pananakit sa iyong kamay kada gabi?)

Yes

☐ No

	1	2	3	4	5	
seldom	○	○	○	○	○	always

10. Have you done any home remedies to alleviate any pain with your hands? (Nakagawa ka na ba ng anumang mga remedyo sa bahay upang maibsan ang anumang sakit sa iyong mga kamay?)

☐ Yes

☐ No

If yes, please state what you do. (Kung oo, mangyaring sabihin kung ano ang iyong ginagawa.)

____

Verified by:

____

Early Detection of Carpal Tunnel Syndrome Using Electromyogram Sensors with an App-Based Monitoring Tool and Applications of Supervised Machine Learning Model for Home-Based Healthcare.

RE-TEST USER ACCEPTABILITY TEST ASSESSMENT FORM

A. Personal Information

1. Name (Optional)

___

2. Age

___

B. User Experience and other information

1. How would you rate the overall usability of the app-based monitoring tool?

   ○ Excellent

   ○ Good

   ○ Fair

   ○ Poor

   ○ Very poor

2. Did you find the app-based monitoring tool easy to navigate and use?

   ○ Yes

   ○ No

3. Were the instructions provided clear and easy to follow?

◯ Yes

◯ No

4. Were you able to set up and use the electromyogram sensors with the app-based

◯ Yes

◯ No

monitoring tool without difficulty?

5. Did the app provide useful information about early detection of carpal tunnel syndrome?
6. Did you feel comfortable using the app and the device?
7. Were there any technical difficulties you encountered while using the app and

◯ Yes

◯ No

◯ Yes

◯ Yes

◯ No

device?

8. How likely are you to continue using the app and the device for monitoring your hand conditions?

- ◯ Very Likely
- ◯ Likely
- ◯ Unlikely
- ◯ Very Unlikely

9. Would you recommend this app and monitoring tool to others for home-based

- ◯ Yes
- ◯ No

healthcare?

10. Additional feedback or suggestions for improving the app and monitoring tool

____

Verified by:

____

ANNEX III

PROGRAM CODES

MACHINE LEARNING SERIAL CODE

(In Python environment)

```
from tensorflow import keras
from tensorflow.keras.optimizers import Adam
import matplotlib.pyplot as plots
from tensorflow.keras.models import Model
from sklearn.metrics import confusion_matrix
import itertools
from tensorflow.keras.preprocessing.image import ImageDataGen
from tensorflow.keras.layers import Dense, GlobalAveragePooling2D



path_train=r'C:\Users\felix\Dropbox\PC\Downloads\TRAIN'
path_valid=r'C:\Users\felix\Dropbox\PC\Downloads\VAL'
path_test=r'C:\Users\felix\Dropbox\PC\Downloads\TEST'

class_label=['Healthy', 'Unhealthy']

train_batch=ImageDataGen(preprocess_funct=keras.applications.vgg16.prepro_in)\
```

```
    .flow_from_directory(path_train,
target_size=(299,299),classes=class_label,b_size=5)

valid_batch=ImageDataGen(preprocess_funct=keras.applications.vgg16.prepro_in)\

    .flow_from_directory(path_valid,
target_size=(299,299),classes=class_label,b_size=5)

test_batches=ImageDataGen(preprocess_funct=keras.applications.vgg16.prepro_in)\

    .flow_from_directory(path_test,
target_size=(299,299),classes=class_label,b_size=5, shuffle=False)


Model_start=keras.applications.vgg16.VGG16(include_top=False,
input_shape=(299,299,3))


z=Model_start.output

z=GlobalAveragePooling2D()(z)

z=Dense(1)(z)

z=Dense(2, activation='sigmoid')(z)

model=Model(inputs=Model_start.input, outputs=z)


Model_start.trainable = False


N=30


history=model.fit_generator(train_batch,
steps_per_epoch=4,validation_data=valid_batch,validation_steps=2,epochs=N,verb
ose=1)
```

```
model.compile(loss='binary_crossentropy',optimizer='adam',metrics=['accuracy'])



model.save('trial.h5')
```

MICROCONTROLLER SERIAL CODES

(In Arduino environment)

```
#include <ESP8266WiFi.h>

#include <Arduino.h>

#include "HTTPRedirect.h"


const char* GScriptId = "YourScriptDeploymentID";

const char* SSID = "YourWiFiSSID";

const char* password = "YourWiFiPassword";


strings payload_base = "{\"command\": \"insert_row\", \"sheet_name\": \"Sheet1\",
\"values\": ";

strings payload = "";

const char* host = "script.google.com";

const int httpsPort = 443;

const char* fingerprint = "";

strings url = strings("/macros/s/") + GScriptId + "/exec";

HTTPRedirect* client = nullptr;
```

```
void setup() {
  Serial.begin(115200);
  delay(100);
  Serial.println('\n');
  WiFi.begin(SSID, password);
  Serial.print("Connecting");
  Serial.print(SSID);
  Serial.println(" …..");

  while (WiFi.status() != WL_CONNECTED) {
    delay(1000);
    Serial.print(".");
  }

  Serial.println('\n');
  Serial.println("Connection established!");
  Serial.print("IP address:\t");
  Serial.println(WiFi.localIP());

  client = new HTTPRedirect(httpsPort);
  client->setInsecure();
```

```
client->setPrintResponseBody(true);
client->setContentTypeHeader("application/json");

Serial.print("Connecting to ");
Serial.println(host);

bool isConnected = false;
for (int i = 0; i < 5; i++) {
  int retval = client->connect(host, httpsPort);
  if (retval == 1) {
    isConnected = true;
    break;
  }
  else
    Serial.println("Failed. Retrying...");
}

if (!isConnected) {
  Serial.print("Failed to connect to server: ");
  Serial.println(host);
  return;
}
```

```
  delete client;

  client = nullptr;

}


void loop() {

  value0++;

  value1 = analogRead(A0);

  value2 = random(0, 100000);


  if (client != nullptr) {

    if (!client->connected()) {

      client->connect(host, httpsPort);

    }

  }

  else {

    Serial.println("Error");

  }


  payload = payload_base + "\"" + strings(value0) + "," + strings(value1) + "," +
strings(value2) + "\"}";


  Serial.println("Publishing.");

  Serial.println(payload);
```

```
  if (client->POST(url, host, payload)) {
    // Handle successful POST response if needed
  }
  else {
    Serial.println("Error");
  }

  delay(100);
}
```

CLOUD-BASED CONVERTER SERIAL CODES

(In Google cloud environment)

```
from google.colab import drive
drive.mount('/content/gdrive')

import os
root_path = '/content/gdrive/MyDrive/GENE_Database'

# Get class names
class_names = sorted(os.listdir(root_path))
n_classes = len(class_names)

# Show
```

```
print(f"Number of Files : {n_classes}\nClass names : {class_names}")



(Gather and save datasets)
from google.colab import auth
auth.authenticate_user()

import gspread
from google.auth import default
creds, _ = default()

gc = gspread.authorize(creds)

worksheet = gc.open('GENE_Datasheet').sheet1



data = worksheet.col_values(4)
import pandas as pd
df = pd.DataFrame({'Data': data})

# Plot the data using matplotlib
import matplotlib.pyplot as plots
```

```
fig, ax = plots.subplots(figsize=(4.8, 2.89))

ax.plot(df['Data'], color='C0', linewidth=1)

ax.tick_params(axis='both', which='both', bottom=False, top=False, left=False,
right=False, labelbottom=False, labelleft=False)

ax.grid(True, axis='y', linestyle='--', linewidth=0.5, alpha=0.5)


# Save the plot in the same Google Drive folder as the GENE-Datasheet

plots.savefig('/content/gdrive/MyDrive/GENE_Database/plot.png', dpi=100)

plots.show()
```

(Read image and save results)

```
import cv2

import tensorflow as tf


CATEGORIES = ["Healthy", "Unhealthy"]  # will use this to convert prediction
num to strings value


def prepare(filepath):

    Size_Image = 50  # 50 in txt-based

    Array_image = cv2.imread(filepath, cv2.IMREAD_GRAYSCALE)

    Array_new = cv2.resize(Array_image, (Size_Image, Size_Image))

    return Array_new.reshape(-1, Size_Image, Size_Image, 1)
```

```
model =
tf.keras.models.load_model('/content/gdrive/MyDrive/GENE_Database/64x300-
CNN.h5')

prediction =
model.predict([prepare('/content/gdrive/MyDrive/GENE_Database/plot.png')])

print(prediction)

print(CATEGORIES[int(prediction[0][0])])

# Open the Google Sheet by name

sheet = gc.open('GENE_Results').sheet1

# Get the next available row on the sheet

next_row = len(sheet.get_all_values()) + 1


prediction_value = CATEGORIES[int(prediction[0][0])]

sheet.update_cell(1, 1, prediction_value)
```

ANNEX IV

DOCUMENTATION

i. Hardware Assembly

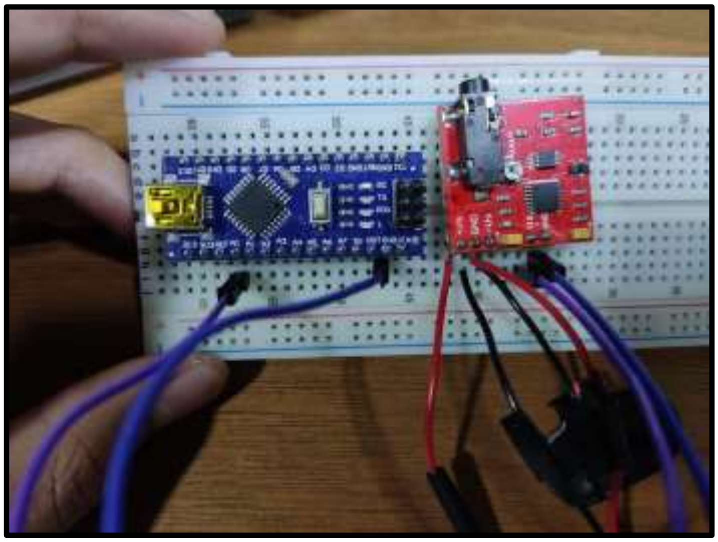


Figure C.1.1 Assembly of the Arduino Uno, EMG Sensors, and Wifi Module

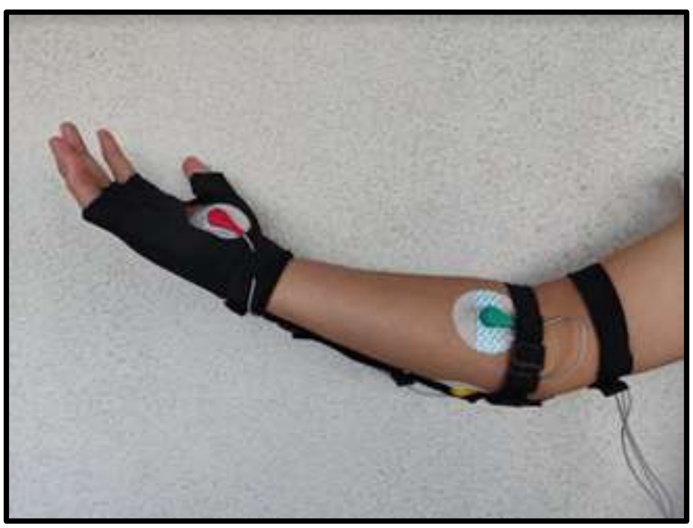


Figure C.1.2 Wearable Device

Figure C.1.3 GENE Device

ii. Software Assembly

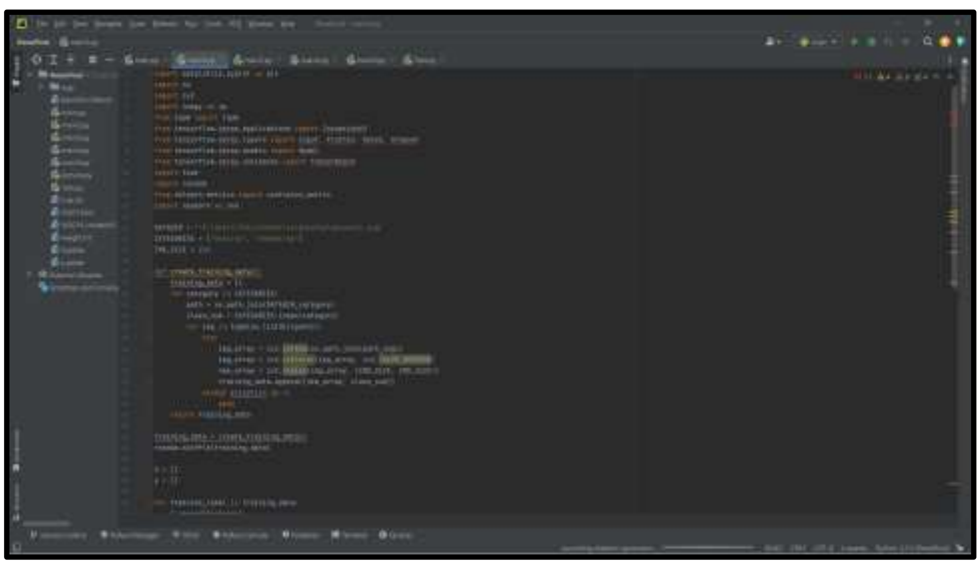


Figure C.2.1 Attempts in Programming of Software Developers

Figure C.2.2 Integration of the Machine Learning to the GENE Device

Figure C.2.3 Creation of the Mobile Application

iii. Deployment Proposal Presentation

Figure C.3.1 Research Deployment Proposal at the Barangay Hall of San Rafael III, Noveleta Cavite with its Officials

Figure C.3.2 PhotoOp with the Officials of the Barangay

iv. Research Deployment

Figure C.4.1 House-to-House Data Gathering at Barangay San Rafael III

Figure C.4.2 Data Gathering at the Baranggay's Covered Court

Figure C.4.3 Photo op with the Medical Professional at the Deployment site

Figure C.4.4 Appreciate 2023

v. Final Defense

Figure C.5.1Photo op with Adviser and Panelists

ANNEX V

PROPONENT’S PROFILE

CABRAL, CALVIN WAYNE P.

CAREER OBJECTIVES

Graduate of Electronics Engineering at Technological University of the Philippines – Manila, seeking opportunity to expand my knowledge in the industry and develop my skills as professional.

PERSONAL INFORMATION

Email: calvinwayne.c@gmail.com
Mobile: +63 9351607178
Address: 382 Camia St. San Rafael III, Noveleta, Cavite

SOFT SKILLS

- Fluency in English
- Communication Skills
- Adaptability
- Teamwork
- Active Listener

CHARACTER REFERENCE

Engr. Glenn C. Virrey, ECT
Faculty, ECE Department
Technological University of the Philippines – Manila
09178797167
glenncalvin_virrey@tup.edu.ph

TECHNICAL SKILLS

- Practiced Simulation Software like Multisim, Proteus, TinkerCad, and Matlab
- Basic Knowledge in Python and HTML
- PCB Circuit and Layout Design
- Wire Crimping
- Experienced in Microsoft Excel

EDUCATION

Bachelor of Science in Electronics Engineering
(2019-2023)
Technological University of the Philippines – Manila
Ayala Boulevard, Ermita, Manila

Science, Technology, Engineering and Mathematics Strand
(2017-2019)
San Sebastian College Recoletos de Cavite
Manila Boulevard, Sta. Cruz, Cavite City, Cavite 4100

ACHIEVEMENTS & CERTIFICATIONS

- **Dean's Lister**
  TUP – Manila
- **Master IP Addressing and Subnetting for CCNA**
  Mnet IT Solutions

I hereby certify that the information provided are true and correct based on my knowledge.

Calvin Wayne P. Cabral
Applicant

EBRON, KENJI GABRIEL B.

CAREER OBJECTIVES

Pursuing data engineering means leveraging my technical skills to design robust data pipelines and infrastructure that support machine learning algorithms, enable data-driven decision-making, and drive innovation in the field of artificial intelligence.

PERSONAL INFORMATION

LinkedIn:
https://www.linkedin.com/in/kenji-ebron/
Mobile: +63 9951347064
Address: Blk 52 Lot 34 Phase 1-C, San Lorenzo South, Santa Rosa Laguna

SOFT SKILLS

- Communication Skills
- Collaboration Skills
- Adaptability Skills
- Emotional Intelligence
- Cultural Sensitivity

CHARACTER REFERENCE

Ericka Bianca Alarilla
Technical Supervisor
Gakken (Philippines), Inc
https://www.linkedin.com/in/ericka-bianca-alarilla-750a69153/

TECHNICAL SKILLS

- Machine Learning: Data Preprocessing, Model Development and Model Evaluation
- Programming: Python, JavaScript, C++
- Artificial Intelligence Development: Natural Language Processing
- Cloud Computing
- Cloud Database

EDUCATION

Bachelor of Science in Electronics Engineering
(2019-2023)
Technological University of the Philippines – Manila
Ayala Boulevard, Ermita, Manila

Science, Technology, Engineering and Mathematics Strand
(2017-2019)
Santa Rosa Science and Technology Highschool
JP Rizal St., Santa Rosa, Laguna, Philippine

ACHIEVEMENTS & CERTIFICATIONS

- **Master IP Addressing and Subnetting for CCNA**
  Mnet IT Solutions
- **Network Security Expert Level 1, 2 and 3: Certified Associate**
  Fortinet
- **Certified in Cybersecurity (CC) Self-Paced Training – 1M**
  (ISC)^2
- **Data Science Foundations**
  Great Learning Academy
- **(ISC)^2 Candidate**
  (ISC)^2
- **Cyber Security Fundamentals: Advanced Persistent Threats**
  Trend Micro

I hereby certify that the information provided are true and correct based on my knowledge.

Kenji Gabriel B. Ebron
Applicant

JIMENEZ, LEANN CYRILLE A.

TECHNICAL SKILLS

- PCB Circuit Design
- PCB Layout Design
- Proficient in Canva and Powerpoint Presentations, etc.)
- Video Editing Skills

CAREER OBJECTIVES

Results-driven ECE student seeking a challenging position to apply and expand technical knowledge while acquiring valuable industry experience. Committed to continuous learning, I aim to contribute to innovative projects, collaborate with multidisciplinary teams, and develop expertise in cutting-edge technologies. Seeking opportunities to enhance skills in circuit design and web development with a focus on delivering high-quality solutions that drive technological advancements.

PERSONAL INFORMATION

Email: leanncyrille.jimenez@gmail.com
Mobile: +63 9176938378
Address: Cavite, CALABARZON (Region IV-A)

SOFT SKILLS

- Good Communication Skills
- Time Management
- Adaptability

CHARACTER REFERENCE

Engr. Glenn C. Virrey, ECT
Faculty, ECE Department
Technological University of the Philippines – Manila
09178797167
glenncalvin_virrey@tup.edu.ph

EDUCATION

Bachelor of Science in Electronics Engineering
(2019-2023)
Technological University of the Philippines – Manila
Ayala Boulevard, Ermita, Manila

Science, Technology, Engineering and Mathematics Strand
(2017-2019)
St. Mary Magdalene School
Kawit, Cavite

ACHIEVEMENT & CERTIFICATIONS

- **Dean's Lister**
  TUP - Manila

I hereby certify that the information provided are true and correct based on my knowledge.

Leann Cyrille A. Jimenez
Applicant

NALLOS, JONIE R.

TECHNICAL SKILLS

- Circuit Design and Simulation
- 3D Modelling and Designing using Fusion 360
- Ptoficient in Python and MATLAB Programming
- CCTV, cable and wirings Installation
- Basic Knowledge in implementing network architecture using Cisco Packet Tracer
- Mobile Application Development: Android Studio and Kodular

EDUCATION

Bachelor of Science in Electronics Engineering
(2019-2023)
Technological University of the Philippines – Manila
Ayala Boulevard, Ermita, Manila

Science, Technology, Engineering and Mathematics Strand
(2017-2019)
University of Perpetual Help System JONELTA GMA Campus
Brgy. San Gabriel, General Mariano Alvarez 4117 Cavite

ACHIEVEMENTS & CERTIFICATIONS

- **Master IP Addressing and Subnetting for CCNA**
  Mnet IT Solutions May 2022
- **Fortinet Network Security Expert Level 1:**
  Apr 2023 – Expires Apr 2025
- **Fortinet Network Security Expert Level 2:**
  May 2023 – Expires May 2025
- **Fortinet Network Security Expert Level 3:**
  May 2023 – Expires May 2025
- **Official (ISC)^2 Certified in Cybersecurity (CC) Self-Paced Training – 1M**
  Jun 2023

CAREER OBJECTIVES

Driven by a passion for innovation in electronics engineering, my career objective is to leverage y technical expertise, problem-solving skills, and collaborative mindset to contribute to the development of cutting-edge technologies and solutions.

PERSONAL INFORMATION

LinkedIn:
https://www.linkedin.com/in/jnallos/
Mobile: +63 9351607178
Address: GMA, Cavite

SOFT SKILLS

- Communication Skills
- Adaptability
- Collaboration
- Problem Solving

CHARACTER REFERENCE

Available upon request.

I hereby certify that the information provided are true and correct based on my knowledge.

Jonie R. Nallos
Applicant

THIO-AC, FELIX KENJIE F.

TECHNICAL SKILLS

- Proficient in Python, Java, C, C++
- Machine Learning and Deep Learning Applications
- Cyber Security
- Expertise in IoT-based Applications, Microcontroller projects, and Simulation tools like Octave, Matlab and Proteus

CAREER OBJECTIVES

Passionate Machine Learning Engineer skilled in mathematics, programming, and data analysis. Seeking to design and implement cutting-edge ML models, collaborate with cross-functional teams, and drive innovative solutions for business insights and AI advancements.

PERSONAL INFORMATION

LinkedIn:
https://www.linkedin.com/in/felix-kenjie-thio-ac-4b240b204/
Mobile: +63 9763882829
Address: Blk 11 Lot 2, Siena Villas, Bacoor City Cavite

SOFT SKILLS

- Strong Analytical Skills
- Problem-Solving Ability
- Curiosity and Continuous Learning
- Communication Skills
- Teamwork and Collaboration
- Adaptability
- Persistence and Resilience
- Ethical Considerations

CHARACTER REFERENCE

Ericka Bianca Alarilla
Technical Supervisor
Gakken (Philippines), Inc
https://www.linkedin.com/in/ericka-bianca-alarilla-750a69153/

EDUCATION

Bachelor of Science in Electronics Engineering
(2019-2023)
Technological University of the Philippines – Manila
Ayala Boulevard, Ermita, Manila

Science, Technology, Engineering and Mathematics Strand
(2017-2019)
University of Perpetual Help – La Piñas
Alabang Zapote Avenue, Pamplona 3, La Piñas, Metro Manila

ACHIEVEMENTS & CERTIFICATIONS

- **Master IP Addressing and Subnetting for CCNA**
  Mnet IT Solutions
- **Network Security Expert Level 1, 2 and 3: Certified Associate**
  Fortinet
- **Certified in Cybersecurity (CC) Self-Paced Training – 1M**
  $(ISC)^2$
- **Authored a Journal - "Image Classifier Differentiating Tumour from Healthy MRI Scans Using Convolutional Neural Networks"**
  Published by ARPN Journal of Engineering and Applied Sciences
- **Served as Reviewer in The International Journal of Compputing and Digital Systems**
  University of Bahrain

I hereby certify that the information provided are true and correct based on my knowledge.

Felix Kenjie F. Thio-ac
Applicant

TORRES, MAE FRANCESSE O.

TECHNICAL SKILLS

- Mobile Application Developer: Android Studio and Kodular
- MATLAB, Proteus & Octave Simulations
- Cisco Packet Tracer Simulation
- Knowledgeable with Python and Java Language
- Technical Writing

EDUCATION

Bachelor of Science in Electronics Engineering
(2019-2023)
Technological University of the Philippines – Manila
Ayala Boulevard, Ermita, Manila

Science, Technology, Engineering and Mathematics Strand
(2017-2019)
Angel John Integrated Academy
Lalakhan, Sta. Maria, Bulacan

ACHIEVEMENT & CERTIFICATIONS

- **Master IP Addressing and Subnetting for CCNA**
  Mnet IT Solutions
- **Network Security Expert Level 1, 2 and 3: Certified Associate**
  Fortinet
- **Certified in Cybersecurity (CC) Self-Paced Training – 1M**
  (ISC)^2
- **International Certification Level 1 as Engineering Technology Aide (2019)**
  Royal Institution Singapore
- **(ISC)^2 Candidate**
  (ISC)^2

CAREER OBJECTIVES

To be able to work in a highly organized environment and contribute my knowledge and expertise in the field of electronics and communication.

PERSONAL INFORMATION

LinkedIn:
https://www.linkedin.com/in/mae-francesse-torres-424b99244/
Mobile: +63 9213976215
Address: Tambubong, Bocaue, Bulacan

SOFT SKILLS

- Adaptable
- Curios and Continuous Learning
- Organize and Efficient
- Time Management
- Can work independently or as part of a team
- Communication Skills

CHARACTER REFERENCE

Jon Kenneth Dio
Network Operation Engineer II
Realpage Phils. Inc.
jonkennethdio@gmail.com
09651085834

I hereby certify that the information provided are true and correct based on my knowledge.

Mae Francesse O. Torres
Applicant

ANNEX VI

USER MANUAL

GENE

User Manual

Nervous Breakdown

Table Of Contents

Safety Precautions

Safety First!

Always keep safety first, follow the safety manual to avoid any injury or harm to the users.

Battery

Please use only 9V batteries to avoid the risk of experiencing minor electric shocks and damaging the device.

Remove the batteries when not in use for prolonged periods to ensure safety and prevent any potential hazards or damage.

To ensure optimal device performance, it is advisable to replace batteries regularly to maintain proper functionality.

Temperature

Ensure device safety by storing it in a cool, dry location and preventing exposure to excessive heat or moisture.

Accessories

For your safety and the integrity of the device, please refrain from making any modifications without the explicit consent and knowledge of the researchers.

Physical Damage

Take necessary precautions to protect the device from physical damage. Handle with care, avoid dropping or subjecting it to impact and store it in a secure and stable location when not in use. Damage in the device's circuit may cause malfunctions.

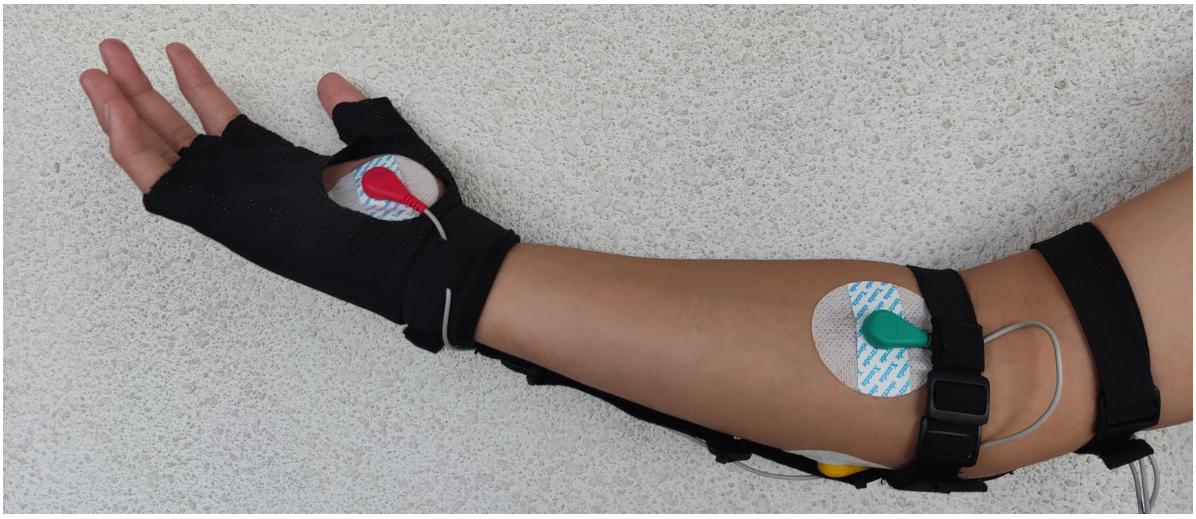
Flammable

For your safety, refrain from using the device in close proximity to flammable objects. Keep a safe distance to prevent potential fire hazards or accidents.

Overview

Introducing GENE, a user-friendly wearable device accompanied by a mobile app that actively monitors and evaluates the health of your hands. By performing hand exercises while using the device, the mobile app collects and analyzes data to provide you with a simple assessment of whether your hands are healthy or not in real-time.

GENE offers an advanced solution to address the growing prevalence of neuropathic hand conditions, such as Carpal Tunnel Syndrome (CTS), by providing proactive hand evaluations even prior to the onset of symptoms. This proactive approach ensures early detection and intervention, enabling individuals to take necessary steps towards maintaining optimal hand health and mitigating the impact of these conditions.

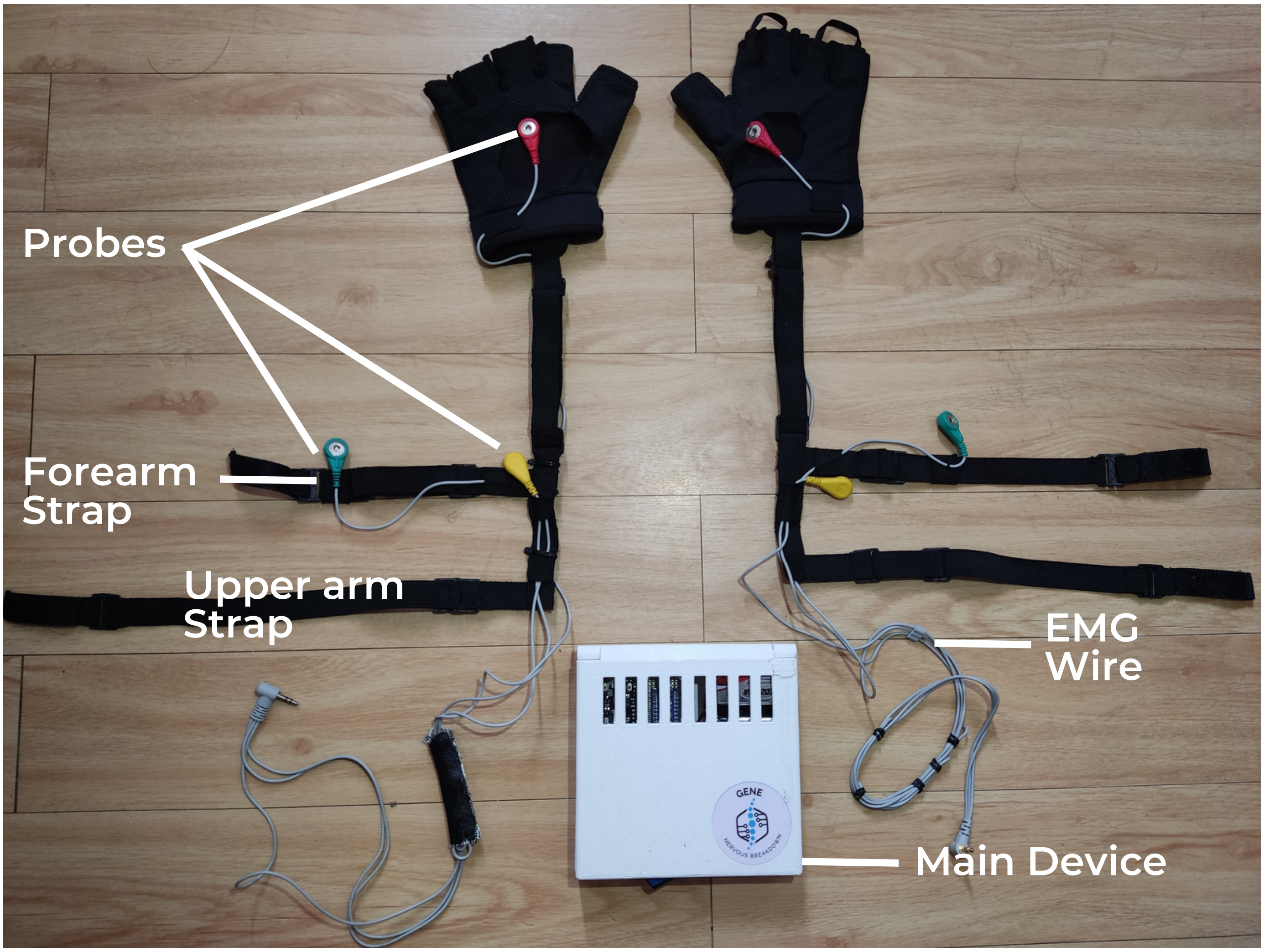


Disclaimer

GENE is designed to provide early identification of potential symptoms associated with CTS. It is important to note that the device's results are for informational purposes only and should not be considered a substitute for professional medical diagnosis or examination. The device is not intended to be used as a treatment method for CTS or any other medical condition. If you suspect you may have CTS or any related concerns, we strongly advise seeking evaluation and guidance from a qualified healthcare professional. The device's results should be interpreted in conjunction with a thorough medical assessment for an accurate diagnosis and appropriate treatment recommendations. The use of this device does not establish a doctor-patient relationship. We disclaim any liability for any reliance placed on the device's results or any damages resulting from the use or interpretation of its findings.

Parts of the Device

2 Wearable Device (Left and Right)



How to Use

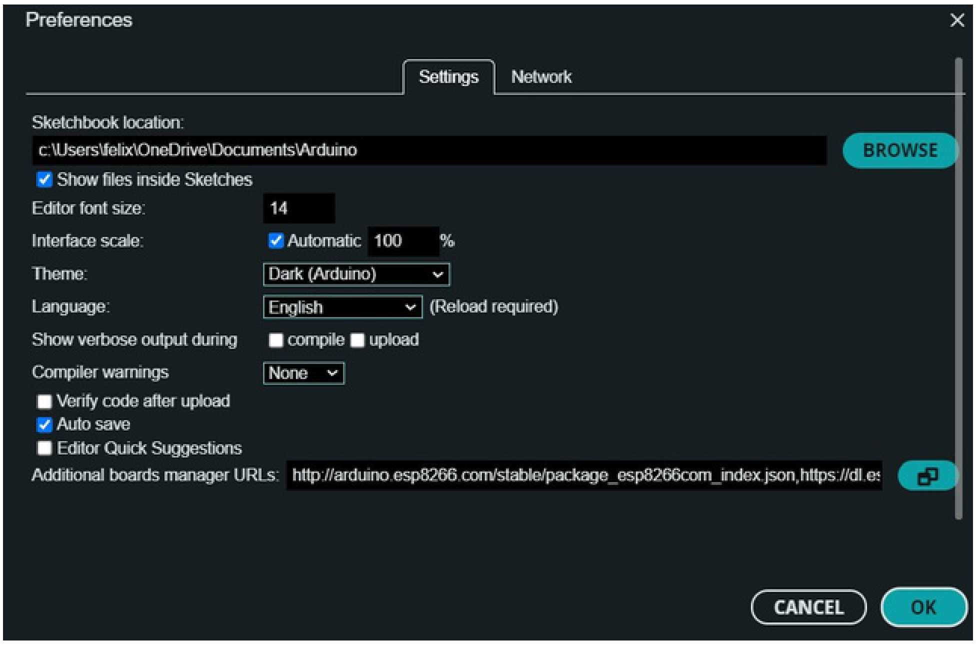
Setting up the Device

Note: Arduino IDE should be installed on your computer to proceed with the re-programming.

1. To start editing the program, open Arduino IDE.
2. Check if ESP8266 is installed in the board manager:

   You can check in the Arduino IDE, go to "File" -> "Preferences." In the "Additional Boards Manager URLs" field, add the following URL: http://arduino.esp8266.com/stable/package_esp8266com_index.json

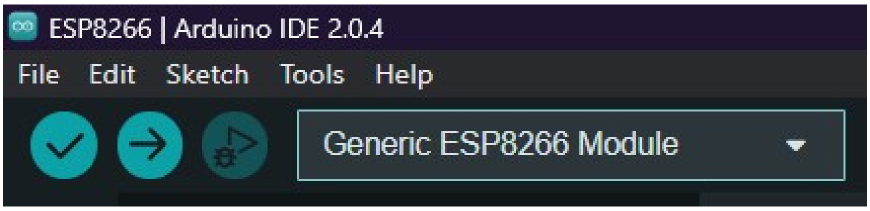
   Click "OK" to save the preferences. Then, go to "Tools" -> "Board" -> "Boards Manager." Search for "ESP8266" and install the "ESP8266 by ESP8266 Community" board.



How to Use

Setting up the Device

3. Select the appropriate board and port. (e.g. ESP8266 - COM10)

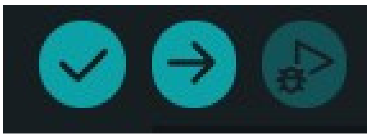


4. In the built-in program, look for the line of code attached below:

```
const char* ssid = "YourWiFiSSID";
const char* password = "YourWiFiPassword";
```

Change “YourWiFiSSID” to the name of the WiFi you will use and “YourWiFiPassword” to its password.

5. Upload the code and verify the connection. Remember to set the available baud rate to 115200.



How to Use

Installing the Mobile App

1. Download the apk file from the google drive link below

   https://drive.google.com/drive/folders/1M87V9kF0uuqxf2vMLnO_m4rp5NYhDrmV

2. Open the downloaded apk file then install.

3. Open the application and start testing

How to Use

Device Placement

1. Choose between the right and left glove depending on which hand will be tested, then attach the EMG patches to the probes. Note that 3 patches are needed for each glove. After all patches are attached, carefully put on the glove and secure it with the wrist strap.

2. For the arm band, resize the base length according to the length of your arm, for the proper length, the upper arm strap should be an inch above the elbow. Once, the base is fit properly, secure with the upper arm strap.

How to Use

Device Placement

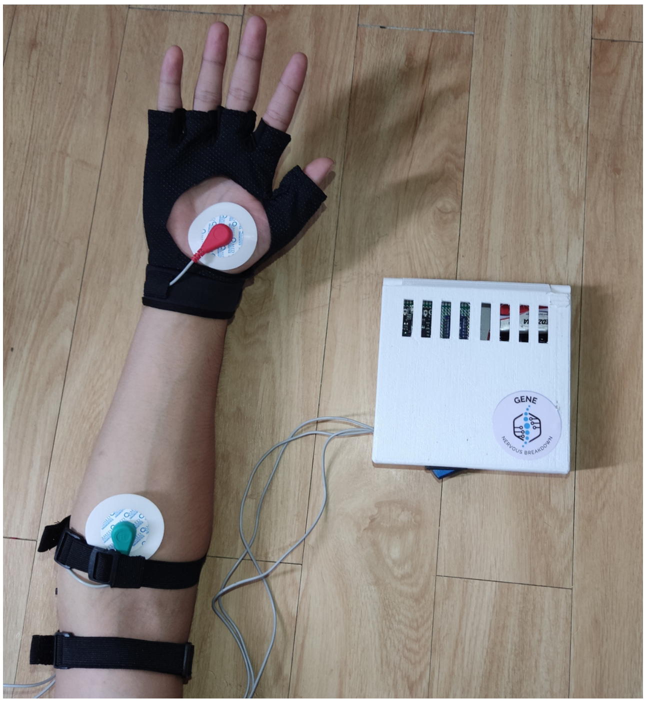
3. Finally, for the forearm strap, attach the EMG patch of the yellow probe to the bone below the elbow, by removing the plastic cover and pressing firmly. Following that, place the patch for the green probe on the inner part of the forearm. For reference, see the figure below to check the probe placements.

4. Once this is done, secure using the forearm strap and go back to the red probe, attach it to the open area of the glove in the palm.

How to Use

Device Placement

5. Lastly, connect the EMG wire to the main device.

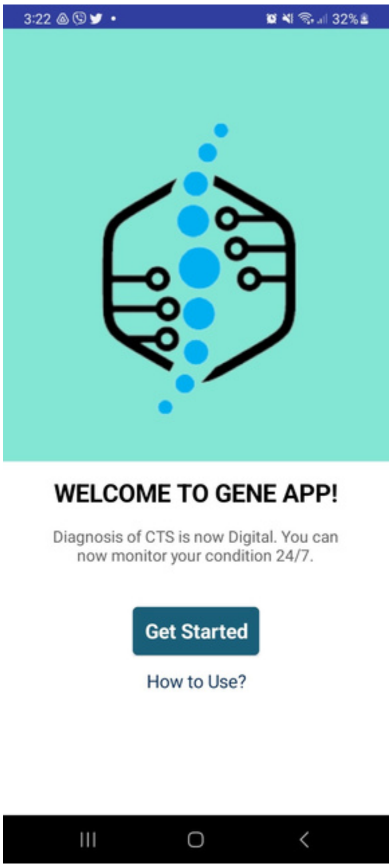


How to Use

Testing

Once the wearable device is all set up and the mobile app is installed we can now start testing

1. Open the mobile application and press Get Started

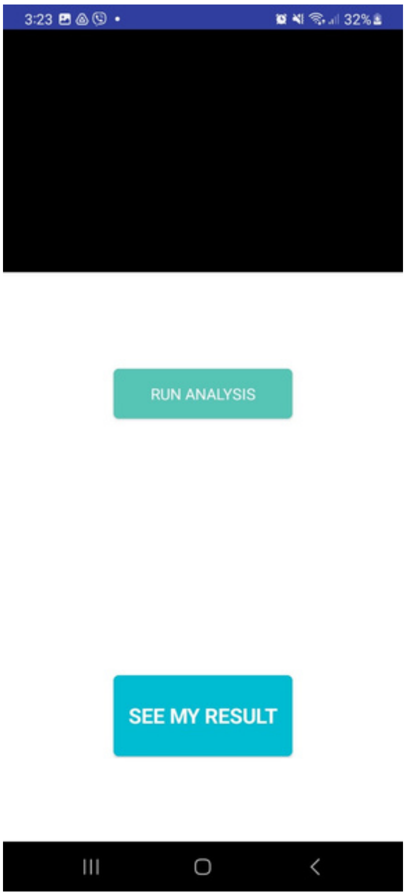


Once you've pressed this button, switch on the main device.

How to Use

Testing

2. From the homepage, the app will direct you to the screen shown below

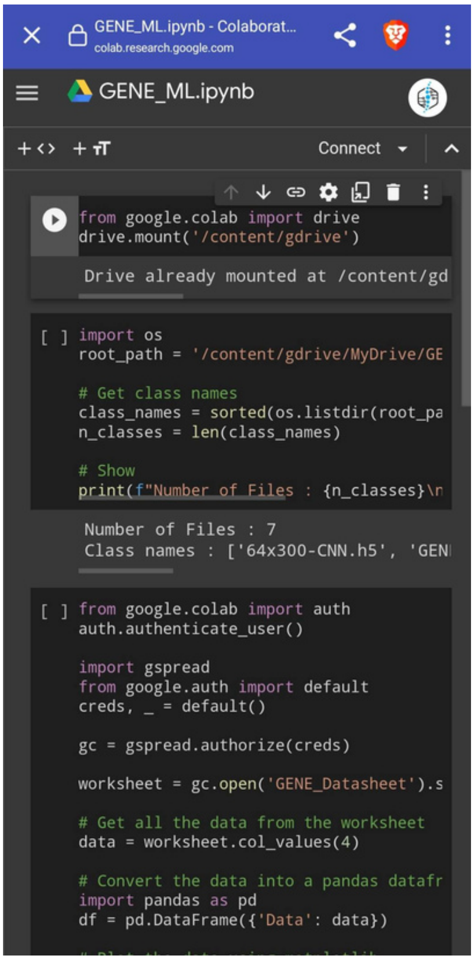


At the top of the screen, you will find a video that you can play. Follow along with the exercises demonstrated in the video as they are designed to assess and evaluate your hand health.

How to Use

Testing

3. Upon completing all the exercises, proceed by clicking on "Run Analysis." This action will prompt the display of the window depicted below.

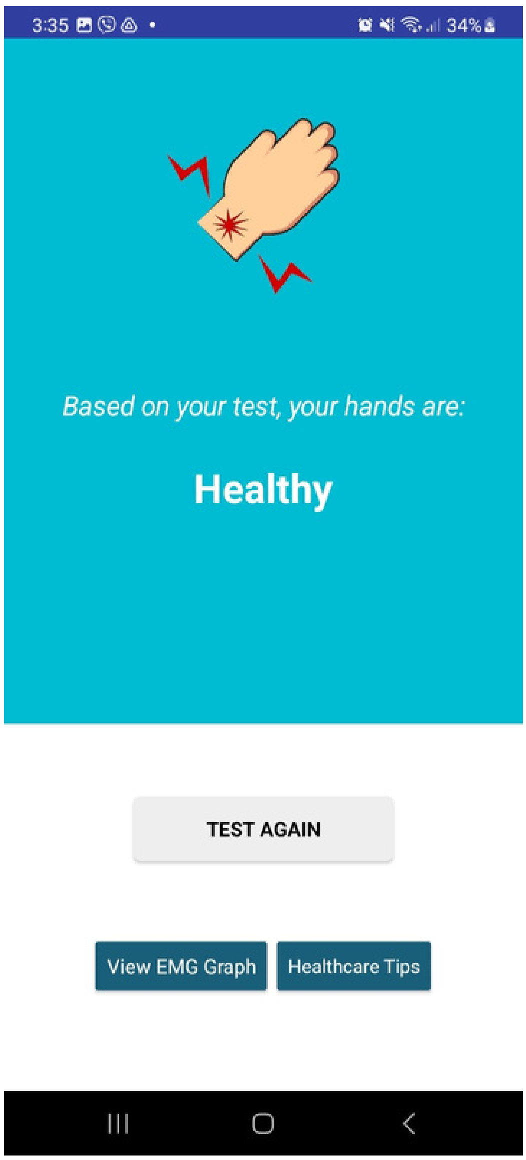


Hit the play/run button on the upper left part of the screen, then close the window.

How to Use

Testing

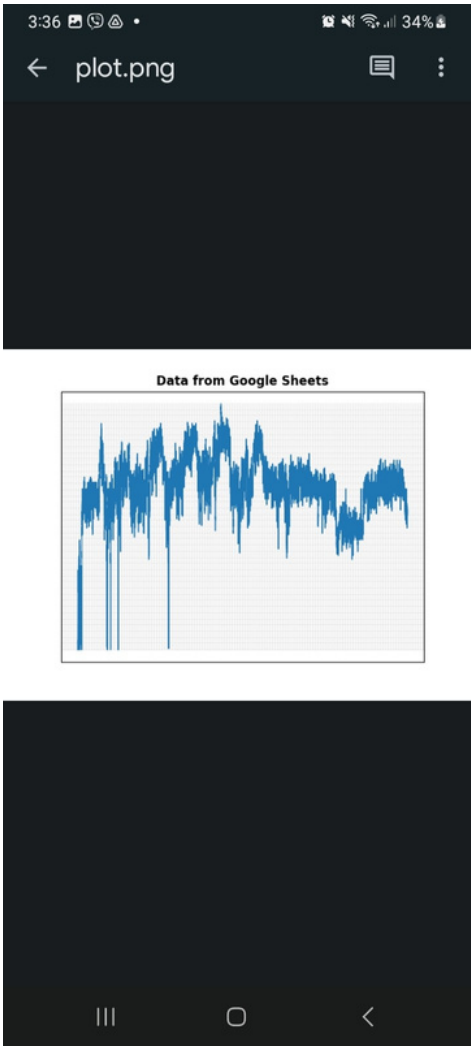
4. Once you navigate back to the application screen, simply tap the 'See my Result' button. Instantly, the app will display your results on the screen, mirroring the format depicted in the image below.

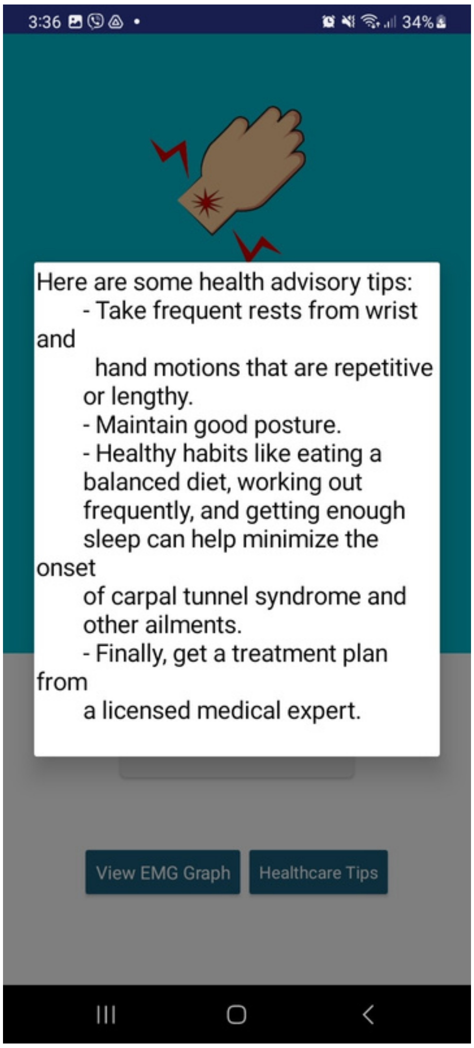


How to Use

Testing

5. Explore further options to enhance your experience. You have the choice to either view your EMG graph, providing visual insights into your hand activity, or access valuable healthcare tips aimed at improving and maintaining optimal hand health.





Maintenance

Keep the device clean and free from dust or debris. Use a soft, dry cloth to gently wipe the surface of the device.

Avoid exposing the device to extreme temperatures, direct sunlight, or excessive humidity. Store it in a cool, dry place when not in use.

Handle the device with care and avoid dropping or subjecting it to impact or rough handling.

Regularly check the device for any signs of damage or wear. If any issues are detected, refrain from using the device and seek professional assistance for repairs or replacements.

Only use 9V batteries and remove when not in use for prolonged periods to ensure safety and prevent any potential hazards or damage.

To ensure optimal device performance, it is advisable to replace batteries regularly to maintain proper functionality.

Keep the device away from water or any liquid sources to prevent damage to its internal components.

Periodically check for software updates to ensure optimal performance and security.

If you encounter any issues or abnormalities with the device's functionality, avoid attempting any unauthorized repairs.

By following these maintenance guidelines, you can prolong the lifespan of your device and ensure its continued performance and reliability.

GENE

TUP MANILA
AYALA BLVD
ERMITA MANILA
(02) 301 3001 loc 501
(+639)995 499 5714

ANNEX VI

MANUAL FOR USER DUPLICATION

GENE

Manual for Duplication of Prototype

Nervous Breakdown

Table Of Contents

Overview

Introducing GENE: a user-friendly wearable device and mobile app that actively monitors and assesses hand health. By performing hand exercises with GENE, the mobile app analyzes data in real-time to provide simple, proactive evaluations of hand health.

GENE addresses Carpal Tunnel Syndrome (CTS) by detecting issues before symptoms appear. This proactive approach enables early intervention, empowering individuals to maintain optimal hand health and minimize the impact of such conditions.

This manual serves as a comprehensive guide, providing detailed explanations of the tools, materials, and step-by-step instructions required to recreate the GENE prototype. By following these instructions, you will be able to develop a fully functional prototype capable of monitoring hand health in real-time.

With the completed prototype, you will have a powerful tool at your disposal to actively monitor and assess hand health, supporting early detection and intervention for a proactive approach to hand care.

User Profile

To create this prototype, user must have knowledge on the following:

Basic Electronics
Understanding the fundamentals of electronics, such as circuitry, components, and wiring, is essential for assembling the prototype.

Sensor Technology
Familiarity with sensor technology, particularly in the context of health monitoring, is crucial for integrating and calibrating the sensors used in the prototype to accurately measure and assess hand health.

Basic Sewing
Proficiency in basic sewing techniques is necessary as the device includes a wearable glove that needs to be hand sewn. Understanding how to handle fabrics, thread needles, and sew stitches will ensure the proper assembly of the glove component.

Prototyping Tools
Competence in using prototyping tools and equipment, such as soldering irons, breadboards, and 3D printers, is advantageous for physically constructing and assembling the wearable device prototype.

Troubleshooting and Debugging
Proficiency in troubleshooting techniques and the ability to debug issues in both hardware and software components are important for identifying and resolving any challenges that may arise during the prototype creation process.

Materials and Tools

Hardware

For the Main Device:

- Arduino Nano
- WiFi Module
- EMG sensor
- PCB
- 3 - 9V battery holders
- 3 - 9V batteries

For the Main Device:

- Garter (3/4 in)
- Slide Buckle (2 cm)
- EMG Wire
- Zip ties
- Velcro Straps (3/4 in)
- Glove (preferably textile gloves)

For the Main Device:

- Soldering Iron
- Soldering Lead
- Soldering Pump
- Solid Wire
- Wire Cutter
- Wire Stripper
- Tweezer
- Medium-sized needle
- Thread
- Scissors
- Sewing Pin

Software

Arduino IDE

Safety Precautions

Electrical Safety

Ensure that all electrical connections are properly insulated and secured to prevent short circuits or electric shocks.

Heat Protection

Take precautions when working with heat sources, such as soldering irons. Use heat-resistant gloves and avoid touching hot surfaces.

Ergonomics

Maintain proper posture and workspace ergonomics to prevent strain or injury. Take regular breaks, stretch, and avoid prolonged periods of repetitive motion.

Sharp Objects

Be cautious when handling sharp tools, such as scissors or wire cutters. Use them carefully and keep them out of reach when not in use.

Follow Instructions

Adhere to the manufacturer's instructions and guidelines for all tools, equipment, and materials used during the prototyping process.

Prototyping Process

Construction of Wearable Glove

This section covers the step-by-step instructions for constructing the wearable glove component of the device.

Preparing the Prototype Materials:

Prototyping Process

Construction of Wearable Glove

1. Create a hole on the palm's thumb area slightly larger than the EMG patch.

2. Gather the following materials: 8 Slider Buckles, 15 pieces of garter, and two pairs of velcro with the following measurements:

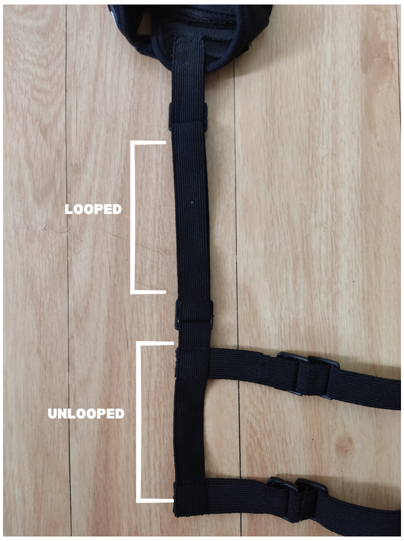
- Garter A: 8cm
- Garter B: 37cm
- Garter C: 9cm
- Garter D: 20.4cm
- Garter E: 9cm
- Garter F: 9cm
- Garter G: 27cm
- Garter H: 9cm
- Garter I-K: 2cm
- Garter L & M: 2.5cm
- Garter N: 4cm
- Garter O: 3cm
- Velcro A & B (Soft Part): 5cm
- Velcro C & D (Rough Part): 5cm

Prototyping Process

Construction of Wearable Glove

Wearable Glove Assembly:

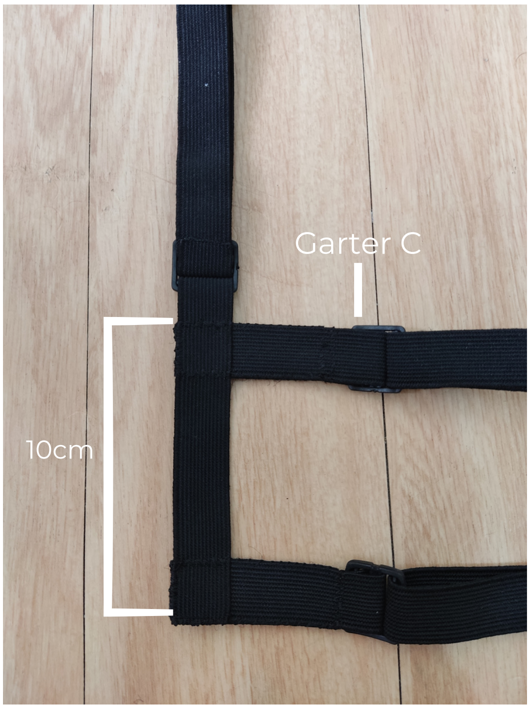
1. Sew a 2cm section of Garter A onto the dorsal wrist area of the glove, creating a loop using a Slider Buckle.



2. Insert Garter B into the Slider Buckle of Garter A, forming a 25cm loop while leaving an extra 12cm unlooped.

Prototyping Process

Construction of Wearable Glove



3. Sew Garter C 10cm away from the end of the unlooped part of Garter B.

4. Attach Velcro A on top of Garter C and sew a Slider Buckle to connect it with Garter D.

Prototyping Process

Construction of Wearable Glove

5. Utilize a Buckle Slider to create an adjustable loop for Garter D and another Buckle Slider to connect it with Garter E.

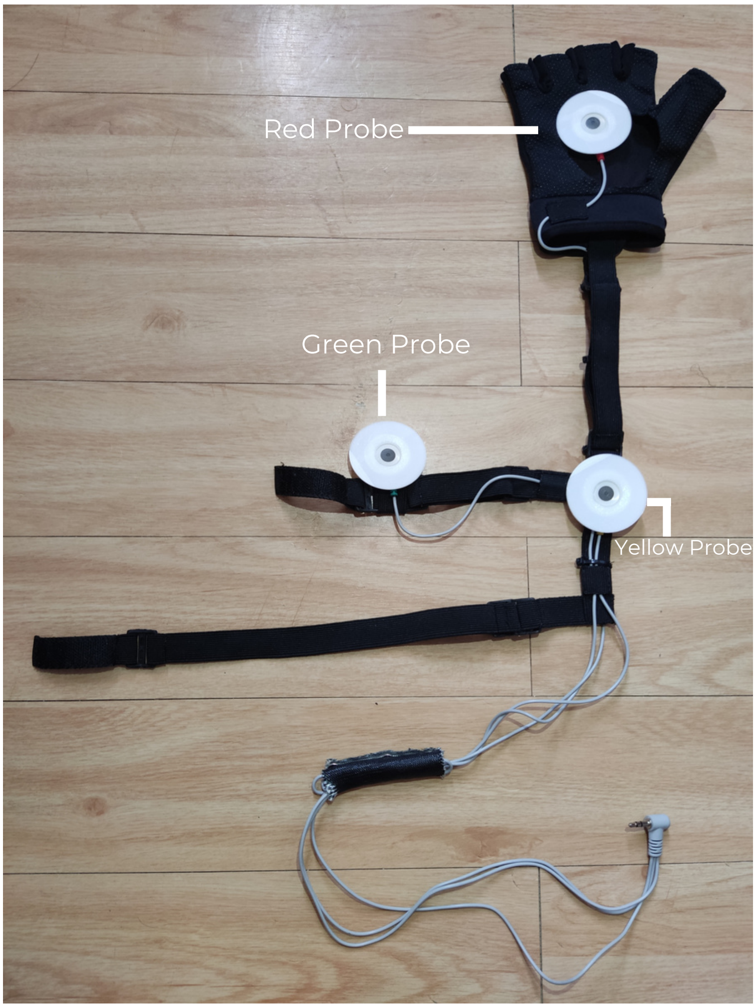
6. Sew Velcro C below Garter E.

Prototyping Process

Construction of Wearable Glove

7. Repeat steps 3 to 6 with Garter F to H at the end of the unlooped part of Garter B.

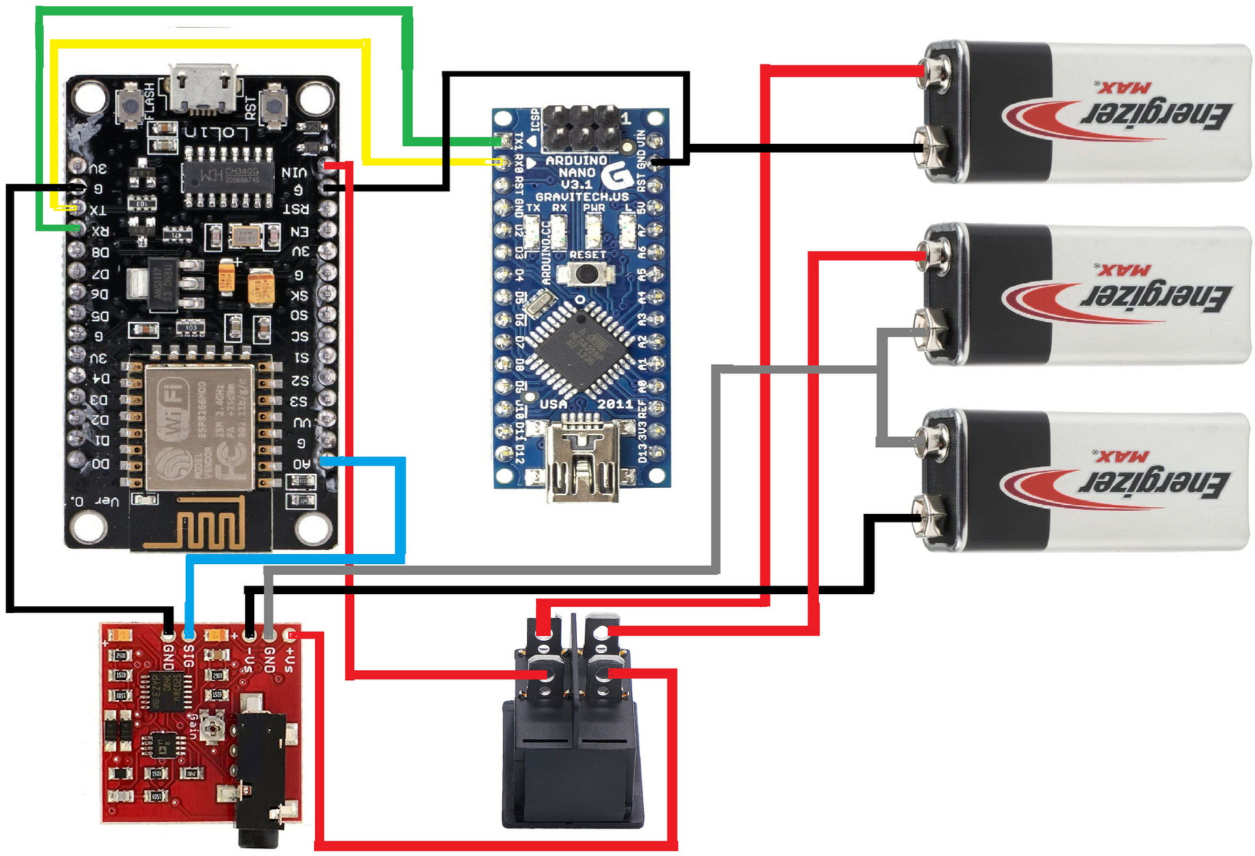
8. Attach the Probes to the whole gloves:



Prototyping Process

Circuitry

In this section, you will learn how to create the electronic circuitry of the main device. It provides instructions for connecting sensors, microcontrollers, and other electronic components.



Prototyping Process

3D Printing of the Case

This section focuses on the 3D printing process for creating the case or enclosure of the device. It covers the preparation of 3D models, selection of appropriate printing materials, recommended printing settings, and post-processing techniques to achieve a sturdy and functional case for housing the electronic components.

1. In this project, the proponents created the design using Autodesk Fusion 360. Make sure to consider the dimensions, features, and any specific requirements for the case.

2. Once the design is final, export it as an STL (Standard Tessellation Language) file. This file format is commonly used in 3D printing and compatible with MakerBot printers.

A design is available below:

https://drive.google.com/drive/folders/1fsBE-p8Zos7ZCuUocjrskm1zB7_P2UJA?usp=sharing

3. Ensure that the MakerBot 3D printer is properly set up and calibrated. This includes making sure the build plate is leveled, the filament is loaded, and the printer is connected to a computer or a network if required.

4. Open the MakerBot slicing software, such as MakerBot Print or MakerBot Desktop. Import the STL file of your case design into the slicing software.

Prototyping Process

3D Printing of the Case

5. Arrange the 3D model within the build volume of the printer. Ensure that it fits properly and that there are no collisions with other parts of the printer.

6. Initiate the print command from the slicing software if the printer is connected. Follow the on-screen instructions to start the printing process.

7. During the printing process, keep an eye on the printer to ensure that everything is running smoothly. Watch for any potential issues like filament jams or warping. Address any problems that may arise.

8. Once the 3D printer completes the printing process, carefully remove the printed case from the build plate. Remove any support structures if applicable.

Software Integration

1. run the following python code with your data sets:

https://pastebin.com/N13UXSVw

2. Open Arduino IDE. Insert the code given in the link below:

https://pastebin.com/AwdGZMpr

3. Download the Necessary Modules
- ESP8266 Module
- JSON Module

4. Connect the device to a computer/laptop using a micro USB cable then upload.

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