Advancing Mobile Healthcare: Integrating Convolutional Neural Networks for Electromyography Data Analysis in Early Detection of Carpal Tunnel Syndrome

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***Abstract*—Surface electromyography (sEMG) measures the electrical activity of muscles and has various applications, including detecting carpal tunnel syndrome (CTS). This research aimed to collect EMG datasets and convert them into graphical images to train a Convolutional Neural Network (CNN) model. This model was integrated into a mobile application to test its accuracy in detecting CTS susceptibility with the aid of medical experts. The findings are compiled into a digital Portable Document Format (PDF). During the device deployment, sixty-two participants were tested to assess whether their hands were healthy or susceptible to CTS. The device's readings were compared to the assessments made by medical professionals, resulting in a specificity of 0.84 and a sensitivity of 0.67. The device demonstrated promising results with an overall accuracy of 71% in determining the condition of an individual's hands. The MyoNerve model, specifically, achieved performance metrics of 71% accuracy, 48% precision, 84% recall, and a 61% F1 score, outperforming the other four models tested in terms of recall and F1 score.**

Keywords— Carpal tunnel syndrome (CTS), electromyography (EMG), electrodiagnostic (EDX), convolutional neural network (CNN), mean absolute value (MAV), root mean square (RMS), diagnostic testing, sensitivity, specificity

I. INTRODUCTION

Advancements in mobile healthcare have increasingly relied on cutting-edge technologies to enhance medical diagnostics and treatment. One notable innovation lies in the integration of Convolutional Neural Networks (CNNs) for electromyography (EMG) data analysis. Muscle contraction generates an electrical signal that contains information about the muscles; this signal is recorded and is referred to as electromyography [1]. Electromyography is a field that examines the electrical activity produced by muscles, aiding in the understanding of muscle function and changes over time, and contributing to studies of the neuromuscular system. A crucial part of this process is feature extraction, which involves identifying and extracting the most useful information from the electromyography signals [2]. By using convolutional neural networks (CNNs), deep features can be extracted from EMG signals to classify actions. CNNs are effective because their local connections and weight sharing provide good translation invariance. When EMG signals are used in modeling electromyography signal recognition, the inherent diversity of the signals can be managed through the invariance provided by convolutions [3].

The integration of convolutional neural networks (CNNs) into electromyography (EMG) data analysis which is embedded to a mobile application is intended to serve solely as an early monitoring and detection tool. It significantly transformed mobile healthcare, particularly in the context of carpal tunnel syndrome (CTS). EMG serves as a vital diagnostic tool for identifying and monitoring neuromuscular disorders such as CTS, which affects the median nerve in the wrist. By incorporating CNNs, renowned for their adeptness in unraveling intricate patterns within complex datasets of gathered EMG signals, we will ascertain whether the recorded data indicates normalcy or the presence of neuropathy, particularly CTS. Mobile healthcare platforms can now swiftly process EMG signals in real-time, facilitating prompt diagnosis and tailored treatment strategies for CTS patients. Ultimately, this integration not only enhances patient outcomes and quality of life by enabling early intervention but also democratizes healthcare access, ensuring that individuals with CTS receive timely and effective care regardless of geographical constraints.

II. BACKGROUND OF THE PROBLEM

Incorporating convolutional neural networks (CNNs) into mobile healthcare signifies a significant leap in medical technology. Electromyography (EMG) data analysis is pivotal for comprehending muscle activity and diagnosing and treating various neuromuscular disorders such as carpal tunnel syndrome. CTS is the prevailing form of nerve entrapment, and according to a study conducted by Werner and Andery, electrodiagnostic (EDX) techniques are a valid and reliable way to diagnose CTS. Abnormalities in the median nerve fibres within the carpal tunnel can be identified through EDX tests, confirming the CTS diagnosis [4]. Traditional methods of EMG analysis typically demand specialized equipment and expertise, constraining accessibility and real-time monitoring capabilities [5]. Nevertheless, integrating CNNs into mobile healthcare platforms has a transformative potential to democratize EMG analysis, allowing for efficient, precise, and portable diagnostic solutions. This integration can potentially overhaul patient care by offering timely insights into neuromuscular health and empowering healthcare professionals and individuals alike to make informed decisions and interventions [6].

In the Philippines, numerous healthcare hurdles persist, notably restricted access to medical facilities, particularly in rural areas [7]. By the fusion of CNNs into electromyography data analysis, healthcare practitioners can remotely oversee patients' muscle activities, enabling early detection and treatment of neuromuscular disorders.

Some studies used a convolutional neural network (CNN) architecture to diagnose CTS through CT scan images. The model was validated with CT images from 53 patients, achieving an accuracy rate of 94%. However, these studies have several limitations: first, they depend on expensive MRI and CT scans that may not always be available; second, they do not consider the overlap of CTS symptoms with other conditions such as cervical radiculopathy, de Quervain tendinopathy, and peripheral neuropathy; and lastly, they overlook clinical, personal, and historical data, which are essential for accurate diagnosis and effective treatment [8]. Hence, this innovation shows promise in improving healthcare delivery, particularly in underserved regions where specialized medical expertise is scarce. Additionally, it empowers Filipinos to proactively manage their health using mobile technology, potentially mitigating healthcare disparities nationwide [9].

III. OBJECTIVES

The primary aim of this study is to incorporate convolutional neural networks into the analysis of electromyography data to identify susceptibility to carpal tunnel syndrome (CTS) in individuals' hands and integrate it into a mobile application. In particular, this study aims to:

1. Develop EMG datasets and transform them into graphical images to train a Convolutional Neural Networks (CNN) model integrated into a mobile application;
2. Test and verify the model's accuracy in detecting CTS susceptibility with the assistance of medical experts.

IV. REVIEW OF RELATED LITERATURE AND STUDIES

A. EMG Data Analysis with Convolutional Neural Networks (CNNs)

Recent electromyography (EMG) signal processing advancements have sparked significant interest in leveraging convolutional neural networks (CNNs) to interpret hand gestures directly from raw EMG signals. Studies such as Yang et al. focus on assessing the effectiveness of different EMG representations, particularly time sequences and frequency spectra, in improving gesture classification accuracy. Their findings suggest that utilizing frequency spectra obtained from raw EMG signals as input to the CNN model yields better results than traditional methods, eliminating the need for preprocessing or feature extraction operations [10]. Similarly, Asif et al. delve into optimizing deep learning architectures, particularly CNNs, for real-time applications in hand gesture recognition using surface EMG (sEMG) data. By fine-tuning hyperparameters and assessing the impact on individual gestures, they identify key motions that consistently outperform others, laying the groundwork for robust myoelectric control systems [11]. Furthermore, Duan et al. explore the application of CNNs in classifying multichannel surface-electromyography (SEMG) signals for gesture motion recognition. Their study underscores the potential of CNNs in effectively extracting intricate features from SEMG signals, offering promising avenues for applications in prosthetic control, rehabilitation, and clinical diagnosis [12]. Overall, these studies highlight the transformative impact of CNN-based approaches in enhancing the accuracy and efficiency of EMG-based gesture recognition systems.

B. Mobile Healthcare Integration of CNN Model

Integrating Convolutional Neural Network (CNN) models into mobile healthcare transforms patient care by providing healthcare professionals with powerful tools to enhance diagnosis and treatment. This innovation allows personalized care, revolutionizing healthcare delivery and improving patient outcomes worldwide. A study conducted by

Ceolini et al. (2019) focuses on using sensor fusion, combining electromyography (EMG) and visual data, to precisely classify hand gestures in mobile applications. The study significantly enhances gesture classification accuracy by integrating EMG signals and visual data from event-based cameras into a framework tailored for mobile devices. Feature extraction techniques such as Mean Absolute Value (MAV) and Root Mean Square (RMS) are employed for EMG signal analysis, leading to impressive results with an 85% accuracy rate. This research highlights the potential of CNN integration in mobile healthcare for personalized medicine applications like calibration and prosthetic control, underscoring its transformative impact on patient care [13]. Moreover, advancements in information technology, as discussed by Sarin Kizhakkepurayil et al. (2009), have led to the development of Location-Based Mobile Healthcare Systems, offering personalized and time-critical services to patients. The integration of CNN models further enhances these systems, enabling healthcare providers to reach patients globally, thus facilitating seamless and efficient healthcare delivery across diverse settings [14].

C. Accuracy Model for CNN machine learning

In machine learning, achieving accuracy is crucial, especially in convolutional neural networks (CNNs). The study evaluates the accuracy exhibited by different convolutional neural network (CNN) models in image classification tasks. The models under scrutiny encompass the VGG-19, VGG-16, Xception, Inception-v3, and LeNet architectures. Notably, VGG-19 and VGG-16 are deep CNNs comprising 19 and 16 layers, respectively, pretrained on the ImageNet database, facilitating the classification of images across 1000 object classes. Similarly [15][16], Xception and Inception-v3 are adept at capturing intricate feature representations across diverse image categories [17][18]. The LeNet architecture, initially devised for Optical Character Recognition (OCR), garners attention for its simplicity and suitability for educational purposes [19]. The study elucidates each model's architectural intricacies, pretrained capabilities, input size specifications, and practical implementation guidelines using MATLAB®. The research looks at different CNN models to find the best one for classifying images. It considers how fast the model works and what it is used for, so it can be helpful in different situations.

D. Diagnostic Testing Accuracy

Accuracy is crucial in medical diagnostics to guarantee efficient patient care. The 2013 publication of Paolo Eusebi's critical work on Diagnostic Accuracy Measures offers priceless insights into evaluating the effectiveness of diagnostic testing. These metrics include accuracy, diagnostic odds ratio, the area under the receiver operating characteristic curve, predictive values, likelihood ratios, sensitivity, and specificity. Sensitivity and specificity are necessary measures of a test's capacity to identify disease and health. In contrast, predictive values evaluate the likelihood of being ill or well in the event of a positive or negative test result. Notably, the scope of the disease and its prevalence have an impact on these metrics. Additionally, overall diagnostic accuracy, reflecting the proportion of correctly classified subjects, is impacted by disease prevalence. Thus, understanding and applying diagnostic accuracy measures are essential for evaluating the efficacy of diagnostic tests in clinical settings [20].

Table 1: 2 × 2 table reporting cross-classification of subjects by index and reference test result (Eusebi, 2013)

	Reference test		
	subjects with the disease	subjects without the disease	total
Index test			
Positive	TP	FP	TP + FP
Negative	FN	TN	FN + TN
Total	TP + FN	FP + TN	Total

True positives (TP), false positives (FP), true negatives (TN), and false negatives (FN) are the four main groups to take into consideration when performing diagnostic testing. False positives are people without the illness whose test results incorrectly appear favorable, while true positives are those with the condition with positive test results. False negatives are people with the illness whose test results incorrectly show negative, whereas true negatives are people without the disease whose test results are negative. These categories provide essential details on whether or not diagnostic tests operate to accurately identify the existence or absence of disease (Eusebi, 2013).

Table 2: Diagnostic accuracy measures (Eusebi, 2013)

Measure	Formula
Sensitivity	TP/(TP + FN)
Specificity	TN/(TN + FP)
PPV	TP/(TP + FP)
NPV	TN/(TN + FN)
LR+	sensitivity/(1 – specificity)
LR–	(1 – sensitivity)/specificity
Accuracy	(TP + TN)/(TP + FP + TN + FN)
DOR	LR+/LR–

It is possible to determine the device's sensitivity, specificity, positive and negative predictive values (PPV, NPV), positive and negative likelihood ratios (LR+, LR–), accuracy, and diagnostic odd ratio (DOR) by obtaining the true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN). To say that the device is functional, the sum of specificity and sensitivity must at least get 1.5. The perfect device for detecting disease must get 2.0 [20].

V. METHODOLOGY

The methodology section provides a systematic overview of the approach to accomplish the study's objectives. It includes collecting and preprocessing electromyography (EMG) data, developing a convolutional neural network (CNN) model specialized for EMG image analysis, integrating it with a mobile application, and thorough evaluation procedures. By adhering to this methodology, the study aims to advance the detection of carpal tunnel syndrome susceptibility while offering a user-friendly solution through a mobile application interface.

Data Collection

This research conducted convenience sampling for demographic data collection. In adherence to data privacy regulations, a consent process was established to obtain respondents' permission to record information, including age, gender, hobbies, occupation, medical history, dominant hand, and EMG readings from their hands.

In this study, researchers utilized the Gravity: Analog EMG Sensor by OYMotion to collect electromyography (EMG) data from the abductor pollicis muscle, where the median nerve is situated. Following the advice of a physical therapist, participants were instructed to perform two routines—rest and thumb opposition—for alternating 15-second intervals, resulting in a complete EMG data collection lasting 1 minute per participant. The dataset comprised EMG data from 148 hands from individuals engaged in hand-intensive labor and computer encoding-related jobs. Under the guidance of a physical therapist, a median compression nerve test was conducted to identify susceptibility to carpal tunnel syndrome (CTS). Consequently, 74 individuals susceptible to CTS and 74 with healthy nerves were selected from both the hand-intensive labor and computer encoding-related workgroups.

Criteria

For individuals engaged in computer encoding-related jobs, the researchers consider the following criteria:

1. *Age Requirement:* Participants must be 18 years old or above.
2. *Duration of Employment:* Participants should have three months or more of employment in computer-aided occupations.
3. *Daily Computer Usage:* Participants should use computers for a significant portion of their daily work activities, typically at least 8 hours daily.
4. *Type of Work:* Participants should be engaged in tasks that primarily involve using computers for work-related activities, such as office tasks, programming, data entry, or other computer-dependent roles.
5. *Consent:* Participants must provide informed consent to participate in the study and agree to undergo EMG data collection procedures.

For individuals engaged in hand-intensive labor, the researchers consider the following criteria:

1. *Age Requirement:* Participants must be 18 years old or above.
2. *Physical Demands*: Participants should be engaged in physically demanding occupations.
3. *Duration of Employment:* Participants should have three months or more of employment in hand-intensive labor.
4. *Type of Tasks:* Participants should be involved in tasks that require significant physical exertion, such as lifting heavy objects, repetitive movements, or exposure to vibrating materials.
5. *Consent:* Participants must provide informed consent to participate in the study and agree to undergo EMG data collection procedures.

Acquiring EMG Data

The device was equipped with electromyogram sensors to collect participants' EMG data. Following the physical therapist's guidance, respondents engaged in rest (A) and thumb opposition (B) activities to capture the electrical activity of the median nerve in their hands. The activities, comprising rest intervals and specific motions, were conducted over 1 minute, with 15-second intervals for rest and thumb opposition. The researchers utilized a data streamer integrated with a spreadsheet to document the electrical muscle activity of the participants.

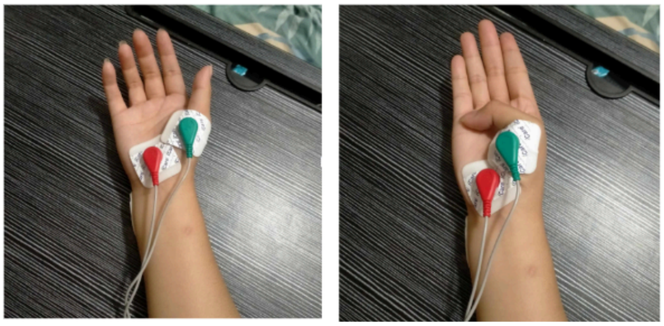


Figure 1: Hand Routines: Rest position (Left); Thumb opposition (Right)

Processing of Data for Machine Learning Model Training

A corresponding CSV file was generated for each instance of electrical activity recorded in a single hand. Subsequently, a data cleaning process was implemented using Python, reducing the dataset to a standardized 1200 rows. The dataset was then transformed into image files, and patch extraction techniques were systematically applied, creating 15 distinctive images for each hand. These images encompassed the complete routine alongside two half-image cropping routines, four quarter-image cropping routines, and eight eighth-image cropping routines, with a dataset comprising records from 146 hands, encompassing 1095 images from normal and susceptible hands. This methodological procedure involved the application of machine learning and artificial intelligence algorithms, processing the initially collected data stored during the input stage. The ultimate goal of this meticulous approach is to develop a diagnostic device tailored to the early detection of carpal tunnel syndrome.

Table 3: Number of Hands and Total images data in Datasets

	Number of Hands	Total Image data
Healthy	73	1095
Susceptible	73	1095

Algorithm Selection

The researchers employed a convolutional neural network (CNN) algorithm, considering the image data file of the EMG data as input. The performance and accuracy rates are contingent on various factors, such as the cleanliness and reliability of the data. Numerous approaches exist to enhance the model's performance and generalizability, each with advantages and disadvantages. Hence, the researchers carefully consider the selection of application-specific techniques.

Model Accuracy Testing

In the initial training phase, the gathered dataset was divided, with 70% allocated to the training set, 20% to the validation set, and 10% to the test set. Preprocessing of the raw data involved resizing and normalizing images to align with the required input size of the model. Subsequently, the architecture of the Convolutional Neural Network (CNN) model is designed, incorporating models like the MyoNerve Model, InceptionV3, VGG16, VGG19, and Xception. The training set was then employed to train the model, and during this process, the test set was crucial for assessing performance and adjusting the model's weights. Following training, a validation set was utilized to comprehensively evaluate the overall performance of the trained model. When deploying the model for predictions, images undergo preprocessing again. The prediction results fall within the range of 0 to 1, where values below 0.5 indicate a normal condition, while values above 0.5 signify a susceptibility state.

Extraction of Root Mean Square (RMS) and Mean Absolute Values (MAV)

In addition to classifying conditions using the ML model, researchers extracted time-domain features, such as the root mean square (RMS) and mean absolute value (MAV), from the raw EMG data. These features are derived from the raw EMG time series and are utilized to examine the association between susceptibility to CTS RMS and MAV. These variables illustrate the functional capabilities of the neuromuscular system during task performance. RMS distributions elucidate the energy levels of action potentials during muscle contractions. RMS is formally defined as

$$RMS = \sqrt{\sum_{i}^{N} x_i^2}$$

On the other hand, MAV acts as an indicator of the magnitude of the EMG data, reflecting the area beneath the rectified EMG signal where negative voltage values are converted to positive. MAV is defined as

$$MAV = \frac{1}{N}\sum_{i}^{N} x_i$$

where xi denotes the EMG signal and N is the length of the EMG signal (Kiran & Uma, 2017).

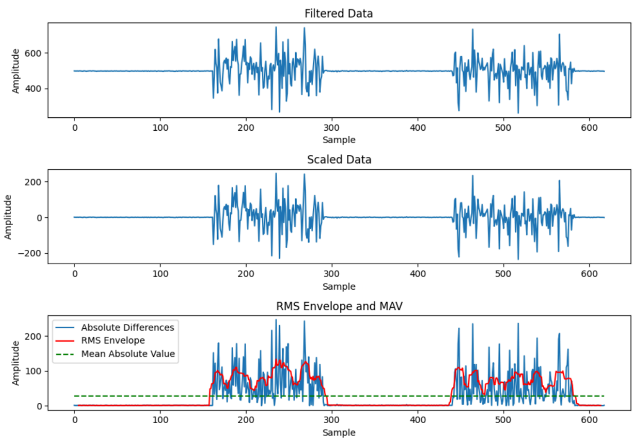


Figure 2: Plot of RMS envelope and MAV

The figure above illustrates the process of identifying the RMS and MAV of an EMG dataset. The raw EMG data underwent preprocessing steps, including data segmentation and outlier filtering, to minimize bias in the graph. Subsequently, the data series were scaled by subtracting the mode from each data point. Following scaling, a Python program computed the RMS and MAV using the above mentioned formula.

Integration with Mobile Application

The main device has the electrodes attached and positioned properly to the surface of the hand around the median nerve to gather the needed EMG data, which is also transmitted to the mobile device it is connected to. The mobile device is installed with the mobile application created for processing and monitoring the raw EMG data.

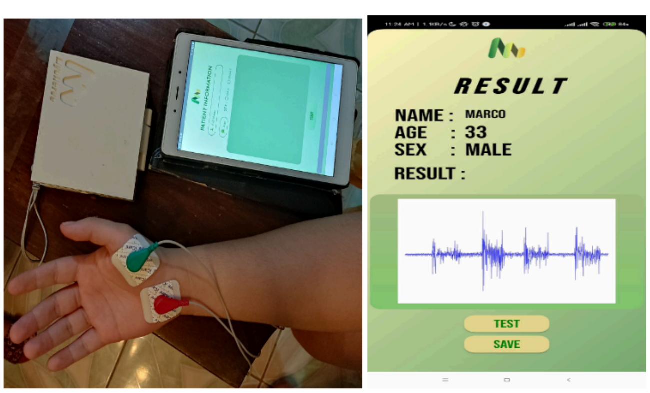


Figure 3: Mobile Application And CNN integration on results.

The mobile application fetches the EMG data and processes it from being a numerical value to a plotted graph in image form. The graph would be tested using the CNN model on the mobile application to convey whether the EMG data gathered is susceptible to neuropathy.

Mobile Application ("MyoNerve App")

The MyoNerve app compose of following features:

1. *Registration Page:* This page shows steps to sign up/ log in and connect a MyoNerve device to the mobile application.

Figure 4: Registration page of MyoNerve App

2. *Menu Page:* This page shows the introductory part of the mobile application. It includes a brief description and steps that the users must complete.

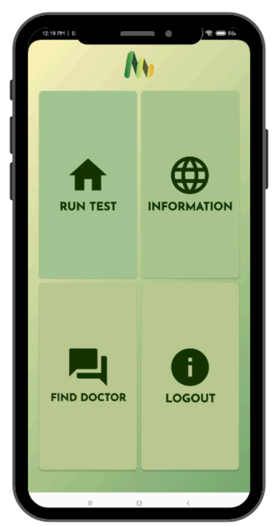


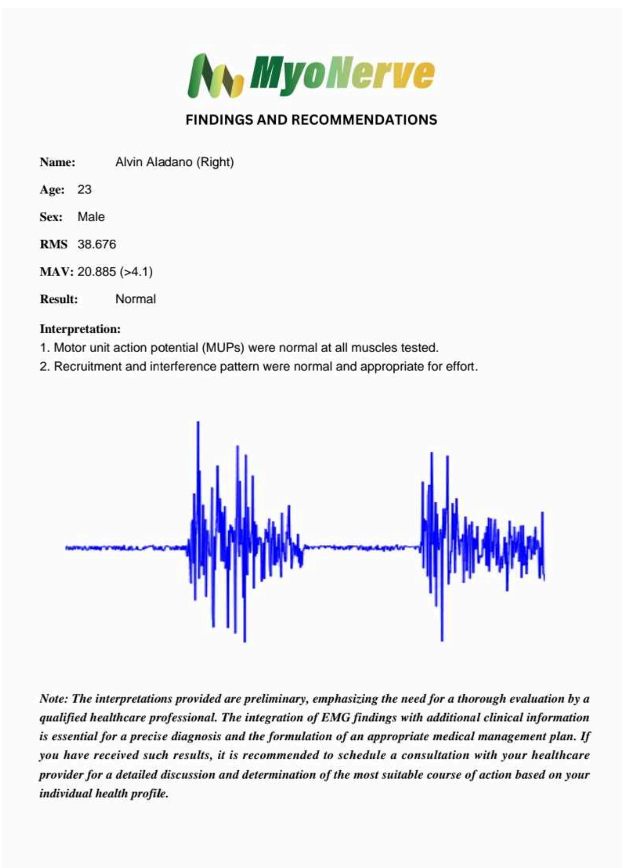
Figure 5: Menu page of MyoNerve App

3. *Test Page:* This page includes the main functionality of the application. The users will be able to know if

they are susceptible to CTS. This page also consists of a summary of the findings.

Figure 6: Test page of MyoNerve App

4. *PDF Result:* A downloadable PDF file shows the results of the CNN model and the interpretation of the gathered EMG data. The interpretation was reviewed by an electromyographer who conducts EMG/NCV tests in a hospital.


MyoNerve

FINDINGS AND RECOMMENDATIONS

Name: Alvin Aladano (Right)

Age: 23

Sex: Male

RMS 38.676

MAV: 20.885 (>4.1)

Result: Normal

Interpretation:
1. Motor unit action potential (MUPs) were normal at all muscles tested.
2. Recruitment and interference pattern were normal and appropriate for effort.

Note: The interpretations provided are preliminary, emphasizing the need for a thorough evaluation by a qualified healthcare professional. The integration of EMG findings with additional clinical information is essential for a precise diagnosis and the formulation of an appropriate medical management plan. If you have received such results, it is recommended to schedule a consultation with your healthcare provider for a detailed discussion and determination of the most suitable course of action based on your individual health profile.

Figure 7: PDF File downloaded on MyoNerve Application

Evaluation of Model Accuracy

In the validation and reliability assessment of the study, the researchers will employ a combination of Diagnostic Testing Accuracy metrics, including Sensitivity, Specificity, Predictive Values, and Likelihood Ratios, in collaboration with medical professionals. Sensitivity measures the ability of the diagnostic device, integrated with the CNN model in the mobile application, to correctly identify individuals with carpal tunnel syndrome (CTS). Specificity evaluates the device's ability to accurately identify individuals without CTS. Predictive Values, including Positive Predictive Value (PPV) and Negative Predictive Value (NPV), provide insights into the likelihood of correct CTS diagnosis based on the device's results. Likelihood Ratios indicate how much the diagnostic device result alters the probability of CTS presence or absence. True positives represent individuals with CTS whose device results are positive, while false positives denote cases where the device erroneously identifies individuals without CTS as positive. True negatives correspond to individuals without CTS whose device results are negative, while false negatives represent cases where the device falsely identifies individuals with CTS as unfavorable. By assessing these metrics with medical professionals' expertise, the researchers aim to validate and ensure the reliability of the diagnostic device integrated with the CNN model for accurate CTS detection. The researchers also used other architectures, such as InceptionV3, VGG16, VGG19, and Xception, to compare their sensitivity, specificity, accuracy and F1-score.

Mobile Application and System Evaluation Form

Professionals fill out the evaluation form here to test its technical usability, user interface and experience, functionality, feat

Table 4: Mobile Application and System Evaluation

Technical Usability					
	1	2	3	4	5
The integration between the EMG device and the mobile application is seamless.					
The data transmission from the EMG device to the mobile app is reliable.					
The app handles data processing efficiently.					
The app's performance remains stable under various conditions.					
The app provides real-time feedback without significant delay.					
User Interface and Experience					
	1	2	3	4	5
The app's user interface design is intuitive and easy to navigate.					
The visual elements in the app are consistent and aesthetically pleasing.					
The app provides clear and concise instructions for users.					
The user experience is smooth and free from bugs.					
The app's accessibility features are adequately implemented.					
Functionality and Features					
	1	2	3	4	5
The app's features are comprehensive and cover all necessary aspects of CTS detection.					
The app accurately interprets data from the EMG device.					
The app's notifications and alerts are timely and useful.					
The app offers useful tips and recommendations based on the data.					
The app's reporting features are informative and easy to understand.					
Security and Privacy					
	1	2	3	4	5
The app ensures that user data is securely transmitted and stored.					
The app's authentication mechanisms are robust and secure.					
The app provides clear information about data usage and privacy policies.					
he app allows users to easily manage their privacy settings.					
Overall Evaluation					
	1	2	3	4	5
The overall architecture of the app is well-designed and scalable.					
The app effectively meets the needs of its intended users.					
The app's performance is satisfactory in real-world scenarios.					
The app demonstrates innovative use of technology for CTS detection.					
I would recommend this app for further development and deployment.					

VI. RESULTS AND DISCUSSION

Utilization of CNNs for EMG Data Analysis and Visualization in Mobile Applications

The researchers have meticulously incorporated various well-established models such as MyoNerve, InceptionV3, VGG16, VGG19, and Xception during the design phase of the Convolutional Neural Network (CNN) architecture. These models were selected for their effectiveness in pattern recognition and adaptability to the constraints of a mobile app environment.

To compare the performance of each model in classifying an individual's condition, the confusion matrices for each model are presented as follows:

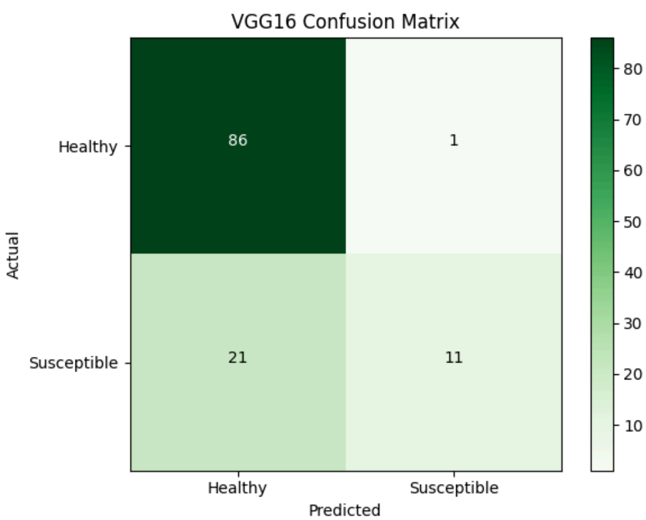


Figure 8: VGG16 Confusion Matrix

The figure above displays the confusion matrix for the VGG16 architecture. It indicates that one patient was recorded as a false negative and 21 as a false positive among the datasets utilized in this model. While this architecture could be considered for deployment within a mobile application, the specificity (0.99) and sensitivity (0.34) are only 1.33, rendering the test less useful.

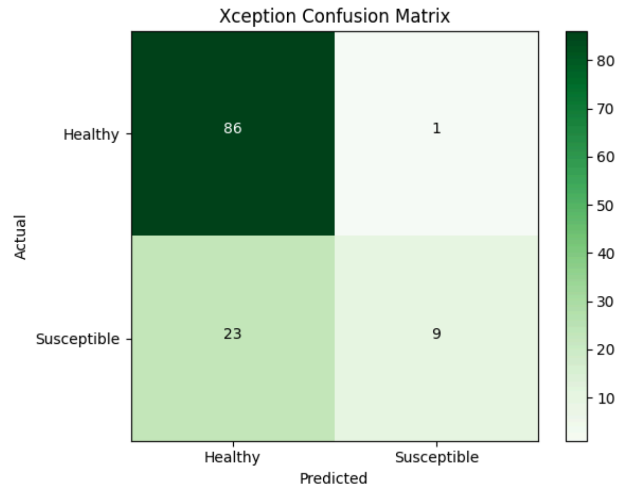


Figure 9: Xception Confusion Matrix

The confusion matrix for the Xception architecture yields a specificity of 0.99 and a sensitivity of 0.28. When these two variables are combined, the sum is 1.27, indicating that this model is less useful in the early detection of carpal tunnel syndrome.

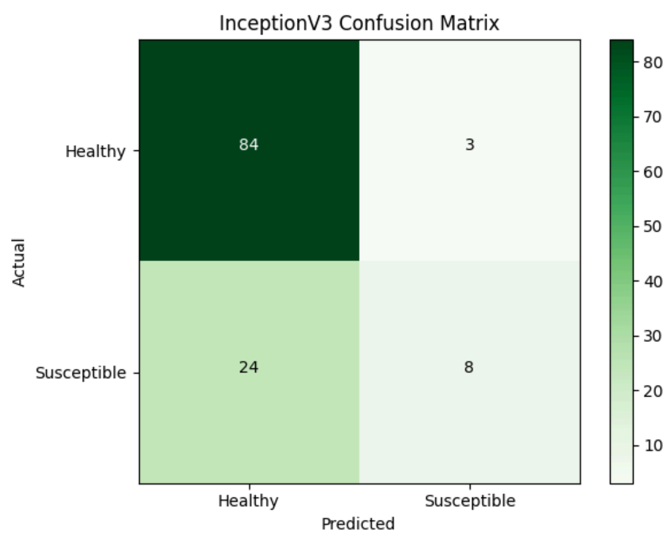


Figure 10: InceptionV3 Confusion Matrix

With three false positives (FP) and 24 false negatives (FN), this model yields a sensitivity of 0.25 and a specificity of 0.97. Adding these two values results in a sum of 1.22, indicating that it does not qualify to help predict an individual's condition.

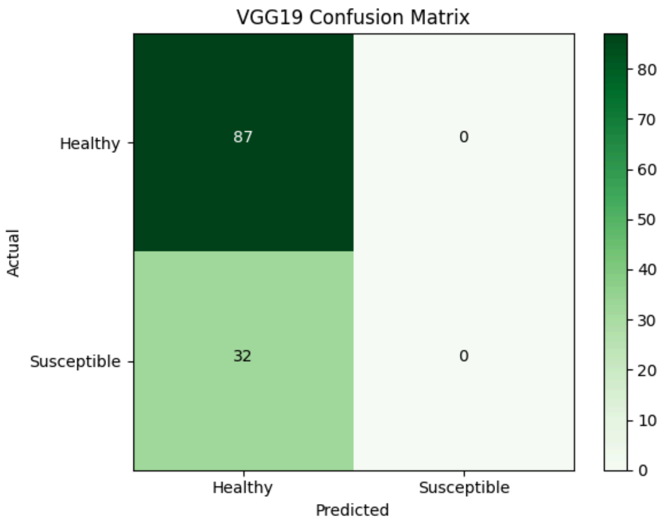


Figure 11: VGG19 Confusion Matrix

The above figure shows the results of feeding the deployment data onto the VGG19 model. It shows that it cannot predict susceptible individuals, resulting in an FN of 32 and a sensitivity of 0.

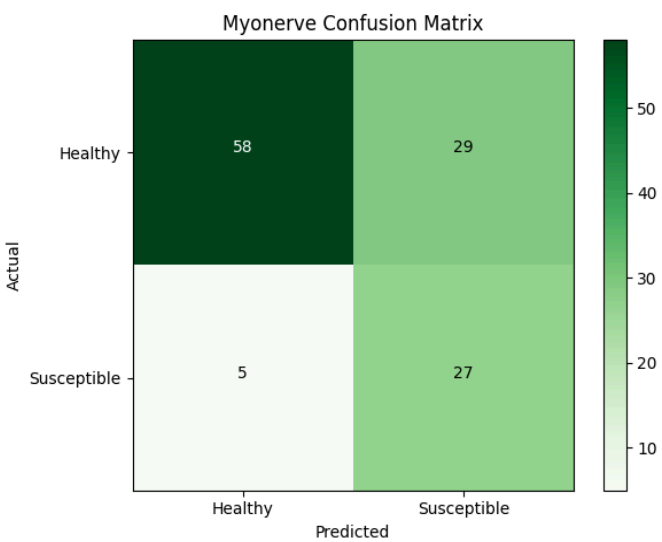


Figure 12: MyoNerve Confusion Matrix

The figure above presents the confusion matrix of the model designed by the researchers MyoNerve. It shows a record of 29 false positives and five false negatives. It results in a combined specificity and sensitivity totaling 1.51, meeting the standard for a usable model for the device

Table 5: Model Architectures' Specificity and Sensitivity

Model	Specificity	Sensitivity	Total	Remarks
VGG16	0.989	0.344	1.332	not functional
Xception	0.989	0.281	1.27	not functional
InceptionV3	0.966	0.25	1.216	not functional
VGG19	1	0	1	not functional
MyoNerve	0.667	0.843	1.51	functional

Based on the table, the only model that qualifies as functional is the MyoNerve model, as its combined specificity and sensitivity total 1.51, meeting the minimum requirement of 1.50 for a medical device. Hence, this architecture is deployed within the mobile application to classify an individual's condition during testing.

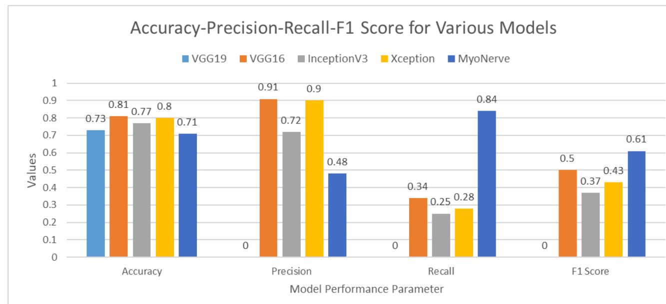


Figure 13: Model Performance of 5 Models

The graph above meticulously presents the performance of various models, including accuracy, precision, recall, and F1 Score. The models chosen for this comprehensive testing were VGG19, VGG16, InceptionV3, Xception, and MyoNerve. It is important to note that the MyoNerve device was specifically designed to utilize the MyoNerve model, adding a layer of precision to our analysis.

The graph shows that MyoNerve got the highest F1 Score and Recall but lowest in Accuracy and Precision. For determining the model performance, the F1 Score is mainly used, and having above 0.50 F1 Score can result in the average performance of the model. Since the F1 Score of MyoNerve is 0.61, which is higher than 0.50, the MyoNerve model is the best model among the other models.

Table 6: Performance Metrics Table

Execution Speed	1-2 minutes
Prediction Speed	1 second

As indicated in the table above, the execution speed of the code responsible for running CNN models in Google Colab ranges from 1 to 2 minutes, with performance influenced by internet speed. However, once the code is executed, the model's prediction time is remarkably swift, taking only one (1) second to determine whether an individual is healthy or susceptible. This prediction result is seamlessly integrated into the mobile application and can be conveniently printed in PDF format.

User-friendly Mobile Application for Electrodiagnostic Data Visualization and Report Generation

Table 7: Mobile Application Information

Application Name	MyoNerve
Storage	365 MB
Operating System	Android
Connectivity	Wi-Fi only
Devices	Smartphone, tablet
Database	Firebase
Paper Size (PDF)	Letter (8.3 x 11 in)

This table presents information about the mobile application designed to be installed on smartphones or tablets. The application requires 365 MB of storage, making it relatively compact and suitable for devices with limited storage capacity. However, since this mobile application version is 1.0, it is only compatible with the Android operating system. It supports Wi-Fi-only connectivity, as it needs to be connected to the same network as the device.

Figure 14: Mobile Application Results Page

One of the critical features of the mobile application is its PDF generation capability, which consolidates all results and interpretations. The generated PDF files are formatted in Letter size (8.3 x 11 inches) and stored in Firebase. Users can retrieve and download these files directly from the mobile application for printing purposes.

Diagnostic Accuracy Test

Table 8: Contingency Table of Test Results Used to Calculate Sensitivity and Specificity

		Physical Therapist Impression		
		Positive (+)	Negative (-)	Total
Test Result	Positive (+)	27	29	56
	Negative (-)	5	58	63
	Total	32	87	119

*Sensitivity = 23/30 = 0.843, specificity = 64/85 = 0.6667

The table above presents the numbers of true positives, false positives, true negatives, and false negatives accumulated from the deployment data. From this data, the device's sensitivity is calculated to be 84%, indicating that it correctly identifies 84% of individuals susceptible to carpal tunnel syndrome. Similarly, the device's specificity is calculated to be 67%, indicating its accuracy in identifying individuals who do not exhibit early symptoms of CTS.

Table 9: Likelihood Ratio Calculations from the Estimates of Sensitivity and Specificity Values

	Specificity	Sensitivity	Positive Predictive Values	Negative Predictive Values	Positive Likelihood Ratio	Negative Likelihood Ratio	Diagnostic Odd Ratio	Accuracy
Test	0.667	0.844	0.482	0.921	2.531	0.234	10.8	0.714

The table above presents a crucial summary of the testing results, providing key insights into the specificity, sensitivity, likelihood ratio, accuracy, and diagnostic odds ratio. These results are of significant importance in the diagnosis and treatment of CTS.

As the data indicates, the device demonstrates a high level of accuracy with a sensitivity of 0.84 and a specificity of 0.67. This means the device is highly effective in identifying individuals with early symptoms of CTS and those without the condition, instilling confidence in its reliability.

Positive and negative predictive values indicate the likelihood that a positive or negative test result is accurate. In this study, representing being healthy or susceptible to CTS, the PPV suggests that 48% of positive results among the deployment data are correct. At the same time, the NPV indicates that 92% of negative results are accurate, meaning individuals genuinely do not manifest CTS symptoms.

The positive likelihood ratio of 2.531 suggests that individuals tested as susceptible to CTS are approximately 2.531 times more likely to have the condition than those tested as healthy. Conversely, the negative likelihood ratio of 0.234 implies that individuals testing negative for the condition are 0.234 times as likely to have it compared to those with a positive test result. These values align with the diagnostic odds ratio of 10.8, indicating that individuals with the condition are approximately 10.8 times more likely to receive a "susceptible" test result than those with healthy hands.

Lastly, the accumulated values support the device's 71.4% accuracy. It suggests a 71.4% chance that the device's presented results are accurate. The sensitivity and specificity must be at least 1.5 for the test to be practical. Wherein the sum of the specificity and sensitivity of the device was 1.51.

Evaluation with Professionals

Figure 15: Evaluation of the MyoNerve Device with Medical Professionals

On the other hand, the researchers consulted with medical professionals, including doctors and physical therapists, to evaluate the device, especially the mobile application. The evaluation comprised technical usability, user interface and experience, functionality and features, security and privacy, and an overall assessment of the MyoNerve device.

Figure 16: Evaluation of the MyoNerve Device with IT Head Engineer

To assess the technical aspects of the mobile application, the researchers chose to evaluate it with an IT supervisor. Based on these evaluations, the device was deemed user-friendly for monitoring results and compliant with standards from the medical professionals to the IT supervisor.

Evaluation Results

The table below shows the overall results of the evaluation. The criteria include technical usability, user experience, functionality and features, security and privacy, and overall assessment. The mean score of each question per criterion was calculated. The review shows that the device software and system received a score of 4.466 for overall evaluation, which satisfies medical and IT professionals regarding the device. However, the researchers addressed the issue of professional concerns.

Table 16: Mean Score per Criterion for Software and System Evaluation

Criteria	Mean
Technical Usability	4.933
User and Experience	4.733
Functionality and Features	4.556
Security and Privacy	4.917
Overall Evaluation	4.466

Based on the comments and suggestions from the professionals, they advised utilizing a variety of tests that can be used to detect carpal tunnel syndrome. In addition, the Data Privacy Act must be included in mobile applications for security purposes. Moreover, inputting detailed instructions into the mobile application is suggested to enhance ease of use. However, the researchers were able to address the suggestions of the professionals.

VII. CONCLUSIONS AND RECOMMENDATIONS

The study was able to make a device accompanied by a mobile application that displays results to users. This app connects to a machine-learning model. The model execution time is approximately 1-2 minutes, while prediction takes only 1 second.

Wherein, the proponents collected EMG datasets and transformed them into graphical images to train a Convolutional Neural Networks (CNN) model integrated into a mobile application. While the execution speed of code for running CNN models may vary, the prediction time is swift, and the results are seamlessly integrated into a mobile application, enhancing the user experience and usability of the system.

Hence, the researchers are able to design a user-authenticated mobile application incorporating a comprehensive result presented in a PDF. The mobile application is compatible with the Android operating system and supports Wi-Fi-only connectivity. Its key feature is the PDF generation capability, which allows users to consolidate and access their results and interpretations conveniently

During the deployment phase, the device demonstrated an accuracy rate of 71%, indicating that most of its results align with the observations made by physical therapists regarding early symptoms related to carpal tunnel syndrome.

To enhance the robustness of the study, the researchers propose several recommendations:

1. Collect a more extensive dataset from diagnosed CTS patients. Additional data will refine the model's accuracy in detecting muscle electrical activity susceptible to CTS, strengthening the device's diagnostic capabilities.
2. Consider using sensory nerve action potential (SNAP) to provide more sensitive and accurate results for muscle activity over the median nerve. Then, Nerve conduction studies (NCV) can be utilized to more sensitively predict early carpal tunnel syndrome in an individual.
3. Incorporate RMS and MAV values into a machine-learning model to enhance the device's predictive capabilities.

VIII. REFERENCES

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