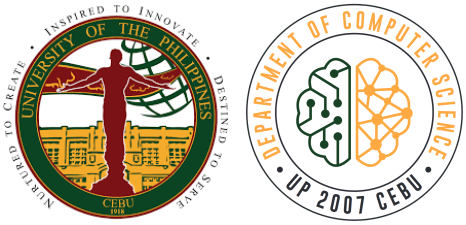

Development of a touch typing trainer with an emphasis on finger and wrist positions

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A Special Project Proposal Presented to the
Faculty of the Department of Computer Science,
University of the Philippines Cebu

In Partial Fulfillment
Of the Requirements for the Degree
Bachelor of Science in Computer Science

Oscar Vian L. Valles
BS Computer Science

Dhong Fhel K. Gom-os
Adviser

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Acronyms

ANSI American National Standards Institute

ISO International Organization for Standardization

JIS Japanese International Standards

WPM Words per Minute

WRNULD Work-related neck and upper limb disorders

Contents

Chapter 1

Introduction

1.1 Background of the Study

There are a lot of educational typing tests available that help people learn touch typing, including Monkeytype, TypeRacer, and Keybr. These typing tests list out words that are then typed out. The inputted keys are then compared to check if the user has typed the expected letter. At the end of the test, the time taken is calculated, and certain metrics are given. These metrics include words per minute (WPM) and accuracy (Bartnik, 2021).

However, this method of examination leaves out a crucial part of typing — ergonomics. Ergonomic typing prevents a lot of health issues in the future like repetitive strain injury or carpal tunnel. One important factor that affects ergonomics is the typing procedure and posture. This means the proper placement of the wrist, hands, and hitting the keys using the right finger that is assigned to the key.

Correct finger placement is usually taught at the beginning using a diagram, with each key being associated with a specific finger. For instance, the letter Q in a QWERTY layout should be hit using the fifth digit of the left hand, and this is shown by coloring the fifth digit and the key Q with the same color or by placing the letters directly on the fingers (Dobson, 2009).

Incorrect finger placement may cause these hand and wrist positions: ulnar deviation, forearm pronation, and wrist extension (Serina et al., 1999). These three are hand and wrist positions that are common in all activities, however, prolonged periods in these positions may cause injuries such as Carpal tunnel syndrome (CTS) (Toosi et al., 2015)

In addition, this type of typing is frequently taught in the beginner level (Donica et al., 2018). This means that there is a need to weed out bad habits that may develop, like using the index finger for pressing the spacebar or backspace. However, it is impractical for an educator to check each student if they are not performing these movements as these may only show for a small period which may not be caught in time.

Thus, there is a need for automatically detecting which finger is used during typing, and for the position of the wrist in relation to the arm. One way to do this is through finger and hand tracking. One solution for tracking is by using image processing and machine learning. An example of this is MediaPipe by Lugaresi et al., 2019.

MediaPipe allows for various applications for machine learning in the field of image processing. This includes, hand tracking, pose estimation, object detection, and others. Another example of a library that allows for hand and finger tracking is OpenCV by Bradski, 2000. This is a tool that simplifies computer vision and image processing. Machine learning can also be used with OpenCV.

1.2 Research Objectives

1.2.1 General Objectives

To create a touch typing trainer that detects poor finger placement and hand position to help develop better typing habits and healthier typing ergonomics.

1.2.2 Specific Objectives

- To develop a program that tracks fingers and hand positions while typing
- To create a subroutine that ascertains which finger was used to type a key
- To detect if incorrect fingers were used to press a key or if the position of the hand in relation to the wrist is problematic
- To assess the accuracy and performance of the developed program's ability to perform the previously stated objectives

- To develop a user-friendly interface for users to train touch typing using the developed program
- To generate key statistics of a user's touch typing performance:
  - Words per Minute
  - Accuracy
  - Finger Placement Accuracy

1.3 Scope and Limitation

This research will focus on typing on a 60% keyboard. Figure 1.1 illustrates this type of keyboard. This type of keyboard only has the alphanumeric part of the keyboard. This limits the number of keys to be checked and the expected movement of the hand. Furthermore, the keycaps will also be of a light color, while the surface that the keyboard rests upon will be of a dark color.

In addition, the keyboard layout will be American National Standards Institute (ANSI). This layout is described by the American National Standards Institute (ANSI INCITS 154-1988, 1999). This is the most common layout in the United States. However, it is also used in numerous English-speaking countries such as the Philippines, Malaysia, and India.

The program will expect the that user has all ten digits and has no hand, finger, or wrist deformities. In addition, only the placement of the hands, fingers, and wrists will be taken into account when determining if the ergonomics of the user while typing is healthy. The program will not check seating position, angle of elbows, and other metrics for an ergonomic typing posture while typing.

Capturing of the video to be analyzed by the program would be limited to a single 480p webcam that is capturing in 24 frames per second. The camera will be pointed downwards facing the keyboard and the hand. This means that the vertical angle of the wrist may not be accurate.

Figure 1.1: A 60% keyboard in ANSI layout. Reprinted from Matt3o. (2014). Filcom MINILA Air pictured with Logitech M705 mouse for scale. Retrieved October 28, 2021, from https://deskthority.net/wiki/File:Filco_MINILA_Air.jpg

1.4 Significance of the Research

This research is beneficial for all users of physical keyboards. These include a vast majority of the population as there are a lot of professions that heavily rely on keyboards. Examples include developers, physicians, educators, accountants. By having better ergonomics while typing, wrist injuries can be prevented, and typing speed may be increased

This research also helps educators, especially early educators teaching beginner typists. By automatically checking for ergonomics, posture, and correct technique, the burden of checking each student is lessened, and directed interventions for bad habits can be easily created as students with these bad habits are easily identified

This research has a direct impact on people that has hand or wrist injuries that are caused by poor typing habits. By correcting these poor habits, pain from these injuries will be lessened, and even be prevented from occurring in the first place. A specific example of this is by reducing ulnar

deviation which affects the nerve that is indicative of CTS (Toosi et al., 2015).

Chapter 2

Preliminary Review of Related Literature

2.1 Keyboard Typing

Keyboard typing is the process of using a keyboard to input characters in a system. In the context of this paper, keyboard typing will refer to the act of using a physical keyboard to input characters in a computer system.

2.1.1 Keyboard Layouts and Form Factors

One key characteristic of a keyboard is its physical attributes. Keyboards come in a lot of layouts and form factors. Keyboard layouts are the shapes, size, and positions of a key on a keyboard while the form factor of a keyboard refers to its shape and dimensions. The form factor also refers to the number of keys included in the keyboard (Parkkinen, 2018). By combining different layouts and form factors, different permutations of a keyboard can be created.

Different keyboard layouts and form factors also produce different effects for the user. This is due to how vastly different some keyboard layouts and form factors are from one another. Some layouts focus on ergonomics, while others focus on typing speed. Some form factors were designed for aesthetics, while others focus on comfort and health. As such, different layouts may affect typing performance, ergonomics, and long-term health effects (Ciobanu et al., 2016).

ANSI and ISO Layout

There are two common keyboard layouts around the world — International Organization for Standardization (ISO) and ANSI.

ANSI INCITS 154-1988 is the standard that first defined the ANSI layout. Figure 2.1 illustrates what the ANSI layout looks like. This layout is also used by countries other than America. Examples of countries that use this layout as its standard is the Philippines, China, and Korea (Apple, 2021). However, these countries also opt to modify the layout by adding extra layers to accommodate other character sets.

ISO/IEC 9995-1:2009 is the standard series that defines a framework that is used to create other layouts. Layouts created from this standard are colloquially called ISO Layouts. Countries around the world use this framework to create layouts that fit the characters in their language. Examples of countries that use this framework to create their own layout are France, Greece, Canada, and Sweden (Apple, 2021).

Both of these layouts usually utilize the same key ordering. This ordering is commonly called QWERTY, based on the first five characters of the first row of this specific layout.

There are other layouts available, however, they are not as common as the two previously mentioned layouts. Examples of this include Japanese International Standards (JIS). Other esoteric layouts, like Tsangan or split-backspace, also exist. These layouts modify the ISO and ANSI standards by adding or removing certain keys to fit the character set of a language, or for additional keys. Other layouts are also exactly the same as ANSI or ISO, however, these layouts change the arrangement of the alphabet within the keyboard.

Despite the ubiquity of these common layouts, studies have shown that these layouts are not ergonomic. The main issue with these layouts is the random configurations of the letters. The randomness of the layout necessitates memorization of the layout which reduces the ease of learning, reduces performance in typing by reducing speed, and increases of typing errors (Ciobanu et al., 2016).

Keyboard Form Factors

There is only one common keyboard form factor used worldwide: the full-size keyboard. This keyboard contains all the keys specified in the keyboard layout. This includes the alphanumeric keys, the function keys, the navigation cluster, and the numpad.

Other common keyboard form factors are based on the full-size keyboard. The name of these layouts, 60%, 75%, and 80% reference the remaining number of keys after cutting a portion off from the full-size keyboard. The 60% keyboards only contain the alphanumeric cluster while the 80% and 75% layouts retain the navigation cluster and the function keys (Parkkinen, 2018). The main draw for using keyboards with reduced sizes is for aesthetics, space constraints, and ergonomics.

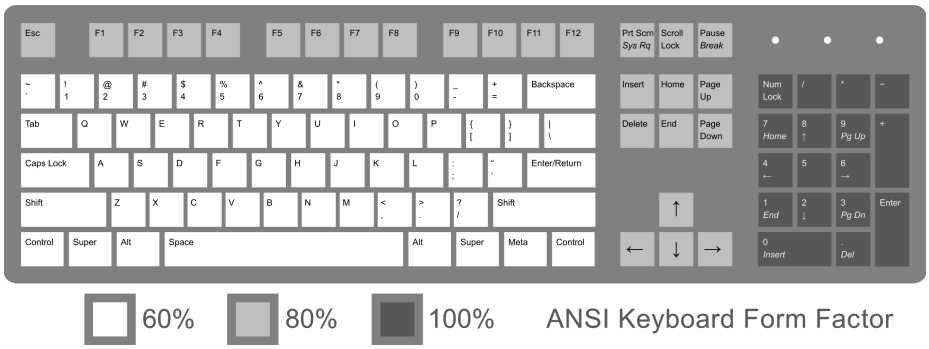

Figure 2.1: ANSI Keyboard layout with form factors. Reprinted from Rumudiez. (2013). Correctly labeled modifier keys for the ANSI Keyboard layout. Retrieved October 18, 2021, from https://commons.wikimedia.org/wiki/File:ANSI_Keyboard_Layout_Diagram_with_Form_Factor.svg

Ergonomic Keyboards Layouts and Form Factors

There have been other keyboard layouts and form factors created to mitigate common issues associated with QWERTY layouts. These include Colemak, Dvorak, and Alphabetical layouts. However, studies have shown that the layout itself does not matter as beginners do not necessarily see the keyboard as a structured set, but rather as a random collection of characters, even if it is alphabetized (Norman & Fisher, 1982),

A different form factor has a great effect on ergonomics. One such example of a form factor is an

ergonomic keyboard developed by Microsoft called Microsoft Natural MultiMedia Keyboard. Ripat et al. used this keyboard in determining that ergonomic keyboards can help in reducing symptoms of Work-related neck and upper limb disorders (WRNULD). Figure 2.2 shows the layout of the Microsoft Natural MultiMedia Keyboard.

Figure 2.2: Microsoft Natural MultiMedia Keyboard. Reprinted from DraugTheWhopper. (2014). MS Natural Multimedia Keyboard. Retrieved October 28, 2021, from https://commons.wikimedia.org/wiki/File:MS_Natural_Multimedia_Keyboard.png

There are other form factors other than the full-size keyboard and variations thereof that focus on ergonomics. One such example is a split keyboard layout where the keyboard is split in half, one for the left hand and one for the right. One such benefit, according to Ergodox EZ, is a more relaxed position due to typing at shoulder width.

2.1.2 Keyboard Typing Metrics

There are numerous metrics used to quantify keyboard typing performance. Two common metrics used in the majority of typing tests include Accuracy and Speed.

Standardized Keyboard Typing Assessments

To be able to measure these metrics, a keyboard typing assessment needs to be done. However, there are no standardized keyboard typing assessments (Donica et al., 2018). As such, teaching methods and assessments, like Keyboarding without Tears, Monkeytype, and Keybr, may produce different metrics for the same typist due to their difference in conducting the assessment.

Speed

Speed, also called as entry rate by Arif and Stuerzlinger, measures the number of characters entered in a specific time frame. The most common metric that measures speed is Words per Minute (WPM). WPM as defined by Arif and Stuerzlinger is:

$$WPM = \frac{|T| - 1}{S} \cdot 60 \cdot \frac{1}{5} \tag{2.1}$$

where, $|T|$ is the length of the text, S is the time in seconds spent writing the text. This time starts directly after the first character has been pressed, and ends when the last letter has been entered. As such, 1 is subtracted from $|T|$, as the time spent to find and press the first character cannot be accurately determined. However, some typing assessments do not subtract 1 from $|T|$. 60 refers to the number of seconds in a minute and $\frac{1}{5}$ normalizes the metric for the average length of words.

Other metrics also measure speed but they aren't as commonly used as WPM. These include Characters per Minute, Gestures per Second, Adjusted Words per Minute, and Keystrokes per Second

Accuracy

Accuracy measures the number of correctly pressed characters in an input string. Accuracy, as defined by Bartnik, is:

$$ACC = \frac{|C|}{|T|} \cdot 100\% \tag{2.2}$$

where $|C|$ is the number of correct characters and $|T|$ is the length of the text.

The inverse of accuracy is error rate, where the number of incorrectly pressed characters is measured instead. Arif and Stuerzlinger describe 5 common error rate metrics: Error Rate, Minimum String Distance Error Rate, Keystroke per Character, Erroneous Keystroke Error Rate, and Total Error Rate.

Limitations of the Metrics

These metrics are all based on the inputted characters by the user. These metrics do not take into account other aspects of keyboard typing such as posture, hand and wrist positions, and finger placement. Consequently, these metrics do not give a full picture of the performance of the person typing and they only provide a cursory view of how a person types.

2.1.3 Keyboard Typing Methodology

Keyboard typing can be accomplished in numerous ways. The main difference between the different methodologies is the number of fingers used when typing and how the typist navigates the keyboard to find the keys. The methodology ranges from Hunt and Peck to Touch Typing, with variations of the two in between.

Hunt and Peck uses one finger on one hand to press a key. This method is aided by using vision to locate the specific key to press (Hoot, 1986). On the other hand, Touch typing uses standard QWERTY mapping to type without using visual cues. (Dobson, 2009) This mapping involves assigning certain fingers to certain keys. Figure 2.3 is the standard QWERTY mapping used for an ANSI layout. Kinesthesis and proprioception are used in locating the keys (Logan et al., 2016).

Figure 2.3: Standard QWERTY mapping for ANSI. Reprinted from Logan, G., Ulrich, J., & Lindsey, D. (2016). Different (key)strokes for different folks: How standard and nonstandard typists balance Fitts' law and Hick's law. *Journal of Experimental Psychology: Human Perception and Performance*, *42*(12), 2084–2102. https://doi.org/10.1037/xhp0000272

2.2 Keyboard Typing in Education

Today, students are expected to type essays, articles, and other submissions using word processors (Poole & Preciado, 2016). Testing is also commonly done using computerized assessments which require the need for keyboards (UMass Amherst, n.d.). As such, there is a need for students to be well versed in keyboard typing and for keyboard typing to be part of the curriculum.

Keyboard typing has been a part of this curriculum for a long time, with studies about effective methods to teach keyboard typing reaching as far back as 1986 (Hoot, 1986). Studies have continued to this day to continue to optimize and improve methods of teaching keyboard typing to students.

These studies start teaching kids in the kindergarten level and the studies try to optimize the teaching methods to improve the speed and accuracy of typing of the learners. By starting to teach touch typing to students early, these students will develop the potential for higher-level keyboard typing (Donica et al., 2018).

2.2.1 Expectations of Keyboard Proficiency

In the United States, keyboard typing is an expected learning outcome for third grade in the Common Core State Standards (Common Core State Standards Initiative (CCSS), 2010). At this grade level, only basic keyboard typing skills are required. By fourth grade, students are expected to have enough proficiency to type one page in one sitting. This is increased to two pages by fifth grade.

In the Philippine context, the Department of Education expects learners with a mental age of 4–6.9 years old to use correct posture and locate characters, learners with a mental age of 7–11.9 are introduced to home row finger placement, and learners with a mental age of 12 and above are expected to "use proper typing technique with efficiency and accuracy without looking at the keyboard" (Department of Education, 2020).

2.2.2 Current Teaching Methods

Current teaching methods involve replicating a given text. Learners then copy the text into a given text field that records the typed characters. Correct and incorrect characters are then identified, and suitable errors are presented. Afterward, metrics, such as WPM, and accuracy are given ("About TypeRacer," 2021; Bartnik, 2021).

Through this process, the learner goes through the three stages of Motor Learning Theory. The student undergoes the cognitive stage where they try to understand and create strategies to accomplish the given task. Then the associative stage follows where the strategies and skills learned from the previous stage are refined. At this stage, the learners are expected to rely less on visuals to locate the keys and more on kinesthesis. By the final stage, the autonomous stage, the learner does not rely on visuals at all and focuses on using kinesthetic feedback to find the keys. By this point, the learner has progressed from using Hunt and Peck, to becoming proficient in touch typing. (Donica et al., 2018)

Keyboarding without Tears

Keyboarding without Tears is a web-based application and curriculum that teaches students touch typing. However, one key differentiator of this curriculum is the usage of a row-based standard

mapping, rather than a column-based standard mapping that is common in other teaching guides. Figure 2.4 shows the standard mapping used in this curriculum.

This curriculum is self-directed and learners can learn at their own pace. At its core, the curriculum is designed to be 36-week long with 5-10 minutes of lessons per day. The lessons in the curriculum follow the three stages of Motor Learning Theory ("Keyboarding Without Tears — K-5," 2020).

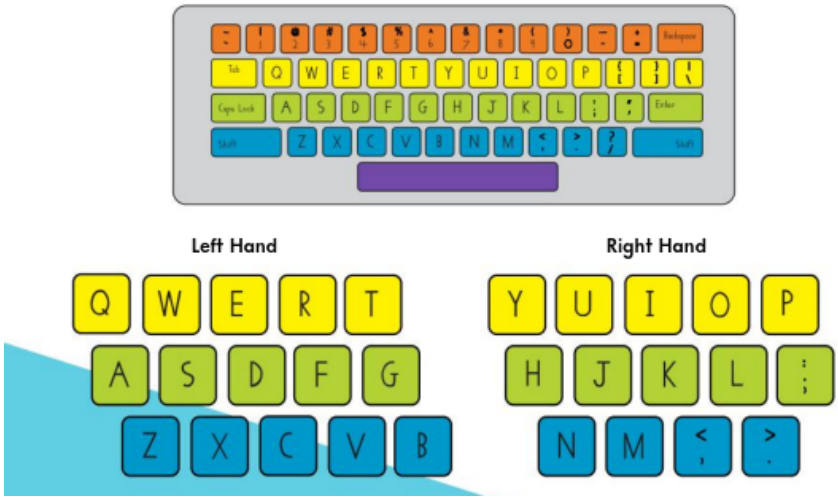

Figure 2.4: Row based standard mapping. Reprinted from Keyboarding Without Tears — K-5. (2020). Retrieved October 26, 2021, from https://issuu.com/handwritingwithouttears/docs/kwtbrochure2020/1

Monkeytype, Typeracer

These two keyboard typing tests are similar. They follow a common experience where users type a predetermined phrase, quote, or random words, and metrics are given after the test. Afterward, the learners may try the test again, or choose another set of words to type. These typing tests do not have a structured curriculum for learning how to touch type. It is left to the learner to practice and learn on their own ("About TypeRacer," 2021; Bartnik, 2021).

Keybr

Keybr is similar to Monkeytype and Typerace, in that they also have the users type a predetermined phrase, quote, or random words. However, this application has more guidance compared to the two. Keybr uses statistics to create typing lessons that are appropriate to the current typing proficiency of the learner. The words selected are random at first, and the skill level of the learner is determined by the performance of the user with these words and characters. The information gathered is then used to generate new words for the next iteration. As an example, if a learner has difficulty in typing the letter q, the next iterations will have a lot of words that contain the letter q.

Statistics from their website show that this learning method is successful, with some learners improving their typing speed by 20–40 WPM ("keybr.com - Typing lessons," 2021).

2.3 Keyboard Typing in Health

There have been a lot of studies that show the effect of keyboard typing, and its associated movements (or lack thereof), has an effect on the human body. These studies have shown that keyboard typing has an effect on our neck, shoulder, upper limb, wrist, arms, and fingers (Baker, Cham, Hale, et al., 2007; Szeto et al., 2005)

2.3.1 Health Issues arising from Keyboard Typing

WRNULD are a common issue that is associated with an elongated length of time maintaining a static posture. When using the computer, the posture commonly adapted by users has the neck and shoulder regions in a static hold for a long time. This results in forward neck flexion and increased muscle tension (Szeto et al., 2005).

In addition, it has been shown that 22% of computer users sustain musculoskeletal disorders of the upper extremity. This includes the neck, shoulder, hands, and wrists. (Gerr et al., 2002)

Carpal tunnel syndrome is also a common issue in the general population. This is caused by the chronic compression of the median nerve. There is a common belief that typing is one main cause

for the disorder (Operations, 2021). There are no definite conclusions if this myth is true, however, a study by Toosi et al. found that typing causes ulnar deviation, especially if done without proper form. This ulnar deviation contributes to the swelling of the median nerve during and after typing. However, the authors noted that it is unclear if this swelling leads to long-term nerve injury.

2.3.2 Finger and Wrist Kinematics

The way people move their hands, wrists, and fingers differ between each person. This can be attributed to the different typing styles each person has. One key difference between people is the angle of the 5th digit.

However, there are some common movements and positions regardless of typing style: flexion, or the curving of the fingers, across the fingers, is decreasing across the hand, with the 2nd digit having the least flexion. This may be due to the instinct to reduce pronation of the hand, which in turn increases the distance of the 2nd digit to the keyboard. In addition, some people isolate or extend one of their thumbs, usually the one not used for pressing a key. This is also true for some people that do not use their 5th digit during typing (Baker, Cham, Cidboy, et al., 2007).

The movement and angle of the wrists also depend on the typing style of the typists. Some people do not reposition their hands, while others do. This difference comes from the way these people reach for certain far-away keys. Some stretch their fingers to reach far-away keys, while others move their entire hand to reach these keys.

For those that reach their keys by stretching their fingers, there is an increased probability that the wrists and fingers adapt non-neutral postures. These include wrist extension, ulnar deviation, and pronation, which may cause musculoskeletal disorders of the upper extremity (Marklin et al., 1999 as cited in Baker, Cham, Cidboy, et al., 2007)

2.4 Finger and Hand Tracking

Finger and Hand tracking is a method of tracking fingers and hands in 3D space using motion capture systems or computer vision. This technique allows computers to perform actions and analyses on

the motions and positions of these body parts.

2.4.1 Types of Tracking

Hardware Aided Solutions

Motion Capture Systems allow for capturing detailed skeletal motion in humans. These systems usually capture full-body motion, focusing on large parts of the human body, such as the torso, limbs, and head.

However, motion capture systems have difficulty in tracking more articulated body parts — with the fingers being one of them. The industry standard for capturing finger movements is through the use of an optical marker-based motion capture system. This is due to its ability to capture natural motion accurately.

This method uses cameras to triangulate the 3D location of markers attached to the limbs of a person. For finger tracking, 13–20 markers are placed on the fingers, and cameras are brought closer to track the small movements of the finger (Wheatland et al., 2015).

But this method is cost-prohibitive, and cannot handle occlusions well. Alexanderson et al. present a method for an optical marker-based motion capture system that can predictably recover from self-occlusion and has a better performance compared to previously used algorithms, however, the issue of cost and self-occlusion still persists.

Bend-sensor gloves are also an option for finger tracking. These gloves have sensors within them that track joint angles in the hand and fingers. One key differentiator of this solution compared to the others is the removal of self-occlusion in the data. As such, this is commonly used in sign language, and gesture recognition due to its accuracy.

However, these gloves need a lot of time to calibrate as cross-coupling of the sensors proves a problem. Cross-coupling is prevalent because the movement of one finger also moves other parts of the hand. These movements may cause a sensor aimed to track a specific movement of a different part of the hand to inadvertently detect a movement when there should be none (Wheatland et al., 2015).

Computer Vision

At its core, Computer Vision aims to perform tasks that the human visual system can do (Huang, 1996). This includes object classification, tracking, and gesture recognition, and face recognition. At the present, most computer vision systems utilize deep learning algorithms, and convolutional networks to gather information from an image, or a set of images. One such example of a convolutional network used in computer vision is Inception by Szegedy et al. which proposes a convolutional neural network architecture for object classification and detection.

2.4.2 Available CV Solutions for Tracking

OpenCV

OpenCV is an open-source computer vision and machine learning software library that houses ≈ 2500 optimized algorithms. This library is widely used by companies, researchers, and open source communities that utilize computer vision and machine learning in their projects. Examples of companies that use OpenCV include Google, Sony, and Honda.

The library has C++, Python, Java, and Matlab interfaces. The library also supports Windows, Linux, Android, and macOS, allowing for great developer experience, and wide deployment capabilities (Bradski, 2000).

MediaPipe

MediaPipe is an open-source computer vision framework that allows developers to create a perception pipeline. This perception pipeline is a directed graph of calculators. Data passes through the graph as packets and a group of packets constitute a data stream. As the data passes through the pipeline, the calculators, produce the desired output.

This framework allows for performant object detection, hand and finger tracking, human pose detection. The framework also allows for combining multiple features, by adding them to the graph as calculators. MediaPipe has C++, Python, JS, and Coral interfaces. It also supports Android and iOS devices (Lugaresi et al., 2019).

MATLAB

MATLAB is a programming platform for the analysis and designing of systems. MATLAB is commonly used by engineers and scientists for computational mathematics (MathWorks, 2021b).

A toolbox offered by MATLAB is the Computer Vision Toolbox that contains algorithms, and functions for use in the development of computer vision, 3D vision, and video processing systems. By using the available algorithms in the toolbox, such as YOLOv2, and ACF, hand detection and gesture recognition is made possible in the platform (MathWorks, 2021a).

2.4.3 Applications

There have been multiple applications and products that utilize hand and finger tracking as their main component.

Dorfmuller-Ulhaas and Schmalstieg, 2001 presents a use case for finger tracking in augmented environments. In the paper, interaction in a virtual environment through the use of gestures. The tracking system uses an optical marker-based motion capture system where the user wears a glove with retroreflective markers.

Hsu et al., 2014 used a Kinect, a 3D sensing device by Microsoft that uses depth data, to track fingers to play virtual instruments. Virtual Pianos and Guitars were created and played with reliable and stable tracking.

Yousaf and Habib, 2014 created a virtual keyboard that operates using finger tracking. The tracking uses the movement of the finger joints as the basis for selecting which key to press. A camera captures the movement, and the resulting video stream is used for hand region detection and finger joint localization. Using probabilistic regional density-based kernel tracking, finger joint trajectories are gathered. Feature vectors are then interpreted from the trajectories. These feature vectors are used in logic-based techniques and Dynamic Bayesian Network for classification, detection, and recognition of keystrokes.

2.5 Summary of the Research Gap

While there are a lot of applications and curriculum aimed at teaching touch typing, there is no automated system available that detects if a person uses the correct finger to press a key.

By having this system, educators can accurately determine if and when a student is having a hard time typing and if these students will need an intervention to correct mistakes.

This is also important because certain movements and hand positions will cause nerve and muscular disorders that will impact the user. By correcting these problematic movements and hand positions, these disorders can be prevented.

Chapter 3

Methodology

3.1 Setup

The experimental setup and configuration will be composed of three elements: the camera, the keyboard, and the environment. Figure 3.3 shows the sketch of the complete experimental setup.

Figure 3.1: Sketch of the experimental setup

3.1.1 Camera

The camera setup will use a single monocular camera positioned in a top-down view. The camera will capture the entirety of the keyboard and the movement of the ten fingers. To do so, it will be mounted on top of the monitor and the camera will point down towards the table. Figure 3.2

illustrates what the camera will capture once placed in its correct position.

Figure 3.2: Keyboard, camera angle, and placement to be used for testing.

The specific camera to be used will be a Logitech C920. Figure 3.3 is a picture of this camera. It is a 3 mega pixel webcam that is capable of capturing color video in 1080p/30fps and 720p/30fps with a diagonal field of view of 78°. This camera has a universal mounting clip that will allow the camera to be correctly positioned within the experimental setup ("Logitech C920 PRO HD Webcam, 1080p Video with Stereo Audio," n.d.).

Figure 3.3: Logitech C920. Reprinted from Logitech C920 PRO HD Webcam, 1080p Video with Stereo Audio. (n.d.). Retrieved January 26, 2022, from https://www.logitech.com/en-ph/products/webcams/c920-pro-hd-webcam.html

3.1.2 Keyboard

The keyboard will be a 60% keyboard as shown in Figure 3.2. This will limit the necessary mapping for the algorithm to the alphanumeric portion of the keyboard. This keyboard choice will also lessen the area that the camera will need to capture, as this keyboard type is considerably smaller compared to a full-size keyboard. The keyboard will have key caps and a case in a light color that will contrast the dark surface that it will be placed on. This is to improve initial keyboard detection. In addition, the keyboard layout will also be ANSI, due to the availability and widespread adoption of the layout in the Philippines.

3.1.3 Environment

The environment the setup would be placed in would be a well lit environment with a light source beside the camera. This light source will evenly light the keyboard and the fingers used for typing. The light source to be used will be a common LED desk lamp rated at 9 Watts with 700 lumens. This light will be white with a color temperature of 6500k.

In addition, the surface where the keyboard is to be placed on will be solid green without any variation of color. This is to improve initial keyboard detection.

3.2 Algorithm

3.2.1 Computer Vision based Keyboard Detection, and Mapping

A computer vision algorithm will be created as a starting point for detecting, and mapping the keyboard within a video. The flowchart of the algorithm is shown in Figure 3.4.

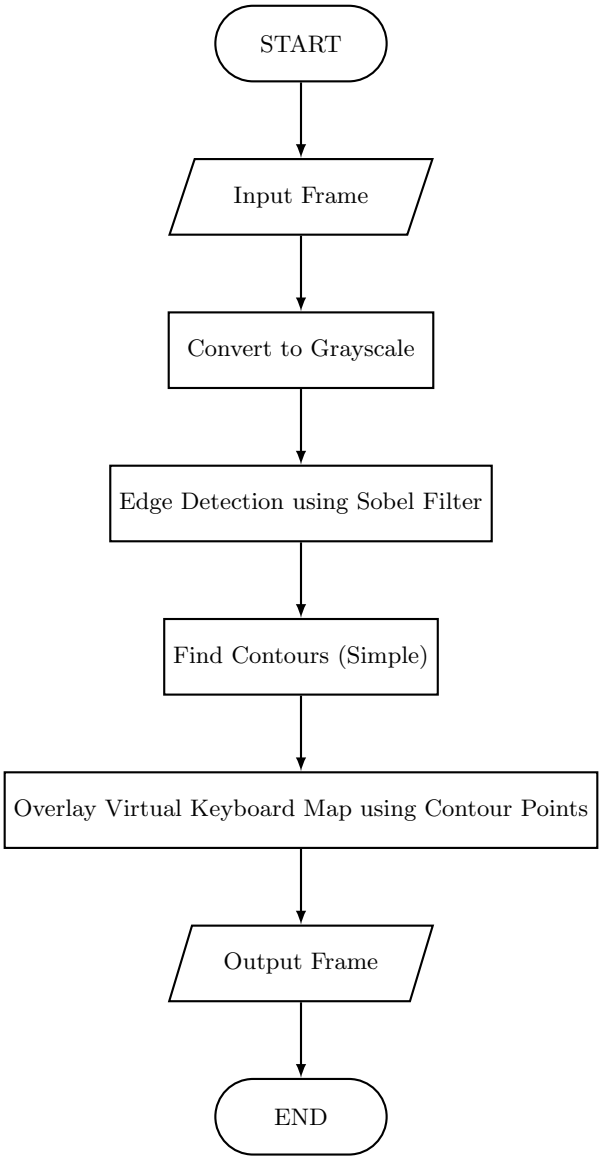

Figure 3.4: Flowchart of Keyboard Detection and Mapping Algorithm

Convert to Grayscale

The frame will be converted to a 256 level grayscale image. This step will be performed because future steps of the algorithm will not require color values to work. In addition, the performance of the following steps will be also improved as the number of dimensions to be analyzed is reduced.

Edge Detection using Sobel Filter

A Sobel Filter is an edge detection filter that uses a 3×3 kernel that is convolved twice. Once horizontally, and another vertically to produce a grayscale image of the outlines within the frame. The kernels used by the Sobel Filter (Sobel, 2014) is shown in Figure 3.5.

$$\begin{bmatrix} +1 & 0 & -1 \\ +2 & 0 & -2 \\ +1 & 0 & -1 \end{bmatrix} \text{ and } \begin{bmatrix} +1 & +2 & +1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

Figure 3.5: Sobel Operator Kernels. Reproduced from Sobel, I. (2014). An Isotropic 3x3 Image Gradient Operator. *Presentation at Stanford A.I. Project 1968*

The expected result of this step is a black and white image that highlights the edges of the keyboard in white.

Find Contours (Simple)

Contours are curves joining all continuous points that have the same color or intensity ("OpenCV: Contours : Getting Started," n.d.). In this algorithm the OpenCV function `findContours` will be used to find the contours of the outlines of the object found using the previous step. This function accepts a contour approximation method as one of its arguments. Two methods are provided by OpenCV, `CHAIN_APPROX_NONE` and `CHAIN_APPORX_SIMPLE`. The former returns all contours in the shape, while the latter removes redundant points and returns the least amount of points that describes the shape. The algorithm will use the latter, as only the extreme edges of the keyboard

needs to be detected. This OpenCV function implements the algorithm of Suzuki and Abe, 1985 in their paper "Topological structural analysis of digitized binary images by border following".

The expected result of this algorithm is four contour points which are positioned on the four edges of the keyboard.

Overlay Virtual Keyboard Map using Contour Points

The virtual keyboard map is a rectangular image that contains individual region of interest (ROI) for each key in a 60% ANSI keyboard. Each key has a corresponding color assigned to it and this color fills the region where this key is located at. Figure 3.6 is the virtual keyboard map.

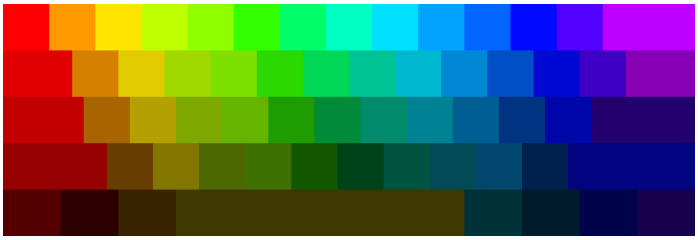

Figure 3.6: Initial Image Map

The virtual map will then be stretched over the object, with the four contour points as the four edges of the virtual keyboard map. The image generated will then be returned as the final output of the graph. Figure 3.7 illustrates this image, and Figure 3.8 shows how accurate the image map is when overlaid over the image.

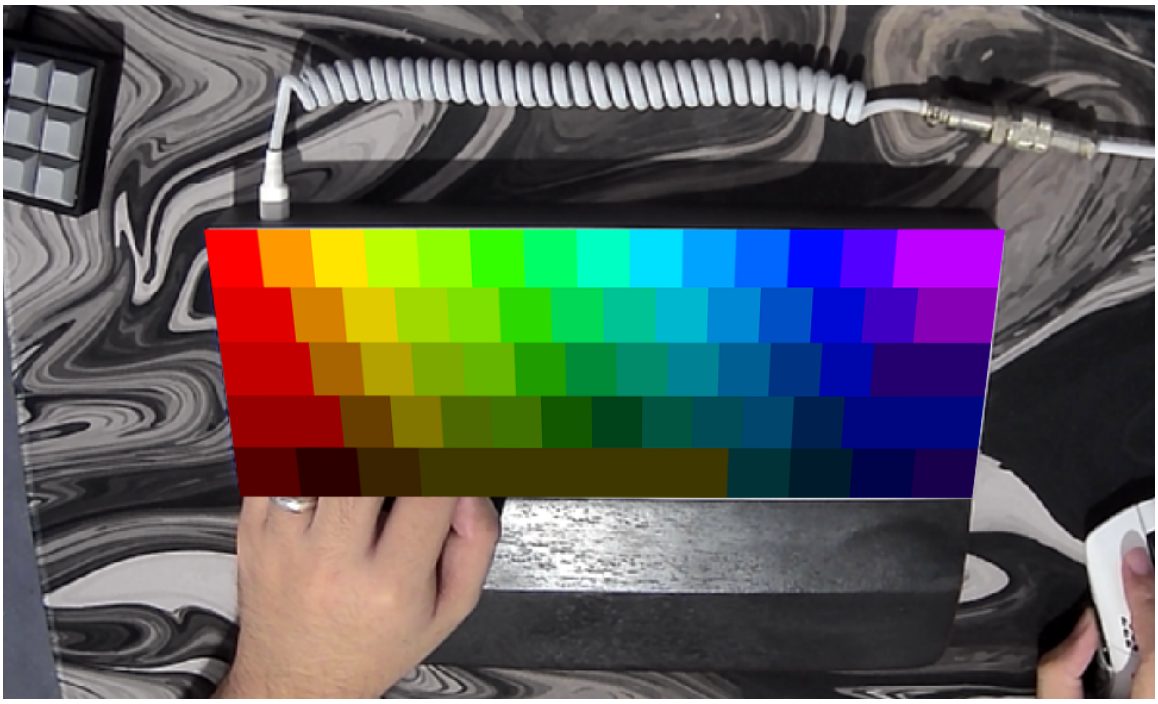

Figure 3.7: Expected output of the algorithm

Figure 3.8: Overlaid image map shown at 60% opacity

3.2.2 Computer Vision based Finger Detection, and Tracking

A computer vision algorithm will be chosen as a starting point for detecting, and tracking fingers within a video. The specific algorithm used for finger detection and tracking will be the solution offered by MediaPipe dubbed MediaPipe Hands. This algorithm is composed of two ML models working in conjunction to be able to detect the different parts of the hands and track them accurately.

Palm Detection Model

The first model, the Palm Detection Model detects the initial hand locations using a single shot detector model based on the paper by Liu et al., 2016. This model achieves an average precision of 95.7% in palm detection (Lugaresi et al., n.d.).

MediaPipe Hands detects the palms first, instead of the whole hands with one model because the hands lack high contrast patterns. This reduces the model's ability to detect the hand with accuracy.

In addition, detecting a palm is simpler compared to detecting hands with articulated fingers since estimating a bounding box around a rigid objects, i.e. a palm, is much simpler. Furthermore, a palm can be modeled using only square anchors reducing the number of anchors by a factor of 3–5 (Lugaresi et al., n.d.).

Hand Landmark Model

After the palms have been detected and an appropriate anchor has been established, the Hand Landmark Model pinpoints 21 3D hand-knuckle coordinates inside the detected hand. This is done using direct coordinate prediction.

This model was trained using 30,000 manually annotated, real-world images with 21 3D hand-knuckle coordinates. Using this information, the model can also accurately add landmarks to partially visible hands and hands with self-occlusion. This is also made possible by the model's consistent internal hand pose representation (Lugaresi et al., n.d.).

3.2.3 Integration for finger-key identification and mapping

The two previously chosen algorithms will be combined to accomplish finger-key identification and mapping. Finger-key identification refers to identifying which finger is used to press which key. As an example, the key Q was pressed with the pinky finger of the left hand.

The integration of the algorithm is a two step process. The first step is to get the mapping of the keyboard using the algorithm shown in Section 3.2.1.

The second step is a continuous loop where the mapping of the keyboard is used in conjunction with the finger tracking algorithm chosen in Section 3.2.2. The flowchart of the algorithm is shown in Figure 3.9

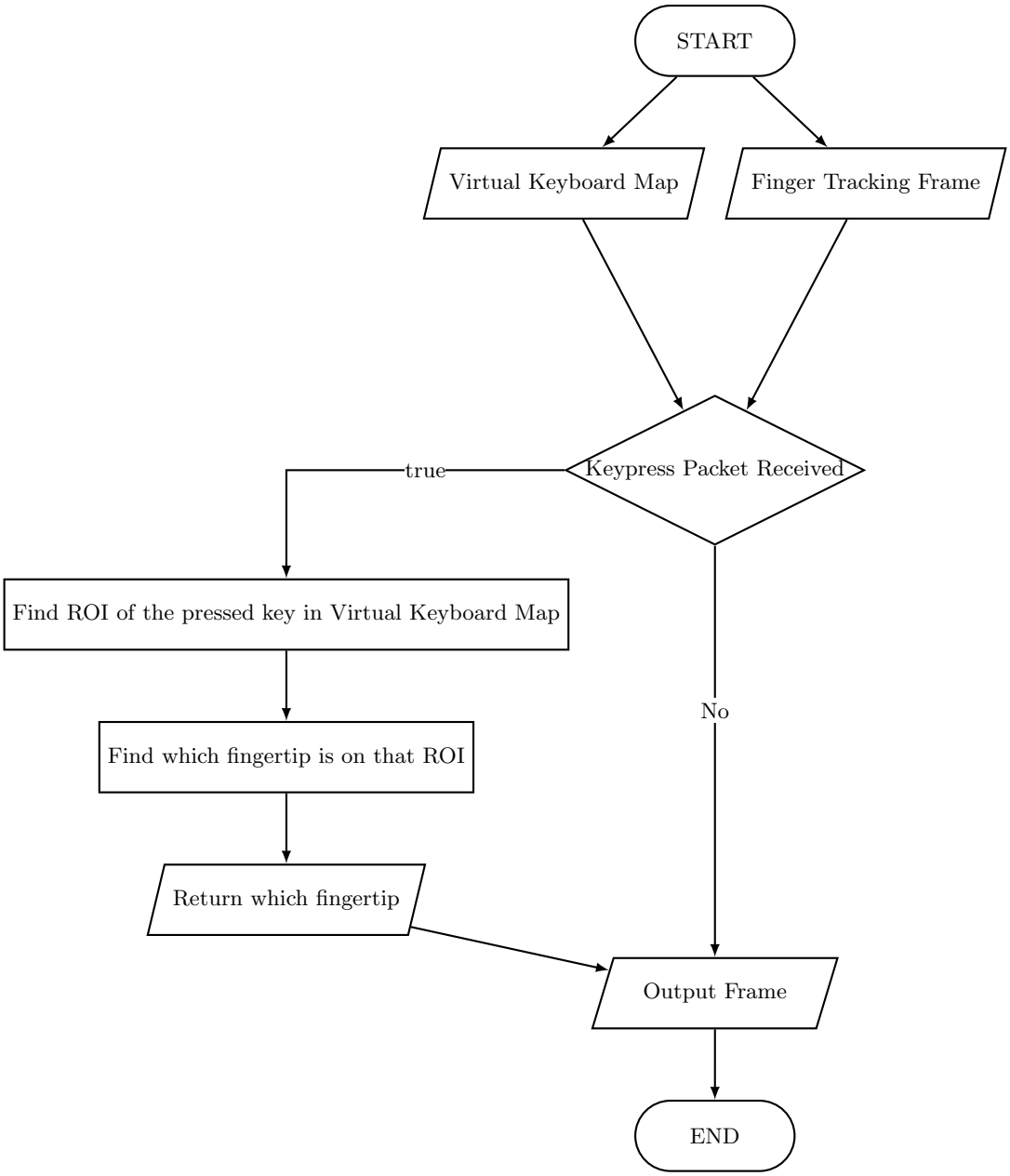

Figure 3.9: Flowchart of the overall flow

Find ROI of the pressend key in Virtual Keyboard Map

Since there is a known color-key mapping based on the Virtual Keyboard Map, the algorithm will find the correct color to search for based on the received keypress packet. This color is isolated from the Virtual Keyboard Map, and the region of interest and its coordinates are obtained. The edges

of this ROI will then be obtained by finding its contours. The specific implementation of this is explained in Section 3.2.1.

The coordinate system will have its origin at the top left, starting at 0, 0. Going to the right increases the value of the x-axis, and going to the bottom increases the value of the y-axis. This will result in a coordinate system that only has positive values with each value corresponding to a pixel.

The expected output of this is four sets of pairs. Each pair corresponds to an edge of the region of interest.

Find which fingertip is on that ROI

The Finger Tracking Frame will contain the pixel positions of each landmark of the hand. For this step, the algorithm will find the landmark which is positioned within the region of interest obtained from the previous step. This will be done using a series of checks.

Each landmark's coordinates will be compared to the coordinates of the edges of the ROI. A landmark will be determined as positioned within the ROI if all of the following conditions are true:

1. In the X axis, the landmark's coordinates is greater than one or both of the two coordinates found of the left side of the ROI
2. In the X axis, the landmark's coordinates is less than one or both of the two coordinates found of the right side of the ROI
3. In the Y axis, the landmark's coordinates is greater than one or both of the two coordinates found of the top side of the ROI
4. In the Y axis, the landmark's coordinates is less than one or both of the two coordinates found of the bottom side of the ROI

These conditions maximize the total area of the ROI and is not strict about exact accuracy. In essence, these conditions will create a perfectly rectangular box that contains the quadrilateral formed by the four points from the previous step.

Return which fingertip

The landmark will then be used to determine which specific finger corresponds to the keypress. Figure 3.10 shows each possible landmark that may be returned from the previous step. This step will then return the name of the landmark, up until the first underscore. As an example, if the landmark found is `MIDDLE_FINGER_TIP`, this step will return `MIDDLE` denoting that the middle finger is the finger that corresponds with the keypress. In addition, the specific hand will also be returned as one of two strings, `Left` and `Right`, since this information is also bundled together with the landmarks.

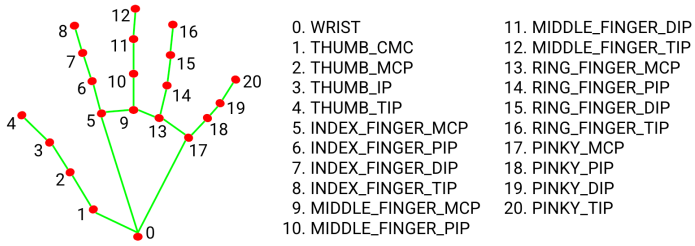

Figure 3.10: Hand landmarks that may be returned by the algorithm. Reproduced from Lugaresi, C., Tang, J., Nash, H., McClanahan, C., Uboweja, E., Hays, M., Zhang, F., Chang, C.-L., Yong, M., Lee, J., Chang, W.-T., Hua, W., Georg, M., & Grundmann, M. (n.d.). Hands. Retrieved January 13, 2022, from https://google.github.io/mediapipe/solutions/hands.html

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3.2.4 Implementation

The previously discussed algorithms will be implemented using Python. The Keyboard Detection, and Mapping Algorithm in Section 3.2.1 will be implemented as a separate submodule in Python using OpenCV.The Finger Detection, and Tracking Solution in Section 3.2.2 will be consumed using the prebuilt Python package offered by the MediaPipe team. Finally, the integration of the two will be done as another separate submodule in Python.

3.3 Trainer

3.3.1 Typing Test Sequences

Typing test sequences are strings that will be used in testing the user in their ability to type. The test sequences that will be used in the trainer will come from text found in the public domain obtained from Project Gutenberg and the Internet Archive. Sentences will be isolated from these text and used as test sequences if they fit a criteria.

The criteria for choosing test sequences is as follows: (1) $\approx 80\%$ of the characters in the keyboard is present in a test sequence. (2) The number of words in a test sequence do not exceed 25. (3) Numbers and punctuations should be present in at least $\approx 30\%$ of the total test sequences.

There will be a total of 10 test sequences that will be gathered. An example test sequence is "What of it, if some old hunks of a sea-captain orders me to get a broom and sweep down the decks?" from Moby Dick by Melville, 2001. The 9 other test sequences can be found in the appendix.

3.3.2 UX/UI design and Front-end development for the touch typing trainer

Design

This design will be based on other type tests such as Monkeytype (Bartnik, 2021), and Keybr ("keybr.com - Typing lessons," 2021), with additional components for showing real-time finger-key identification and mapping. Figure 3.11 and 3.12 illustrates the two main pages of the design. Additional screens, such as historical statistics, in-platform tutorial, and a written guide are shown in the appendix.

Figure 3.11: Test screen of the front-end design

Figure 3.11 has four main components. From the top, the first component is the navigation bar. This directs the user to the different pages within the website. The second component in the upper left displays the number of remaining words to be typed. This is 16 in the example. Below that is the test sequence. This shows the user what characters to type, and highlights mistakes in two distinct colors. Red if the character pressed was incorrect and purple if the character typed was correct, but the finger used to type it is wrong. The last main component in this screen is the keyboard that illustrates the correct finger positioning, with each finger corresponding to a different color.

Figure 3.12: Statistics screen of the front-end design

Figure 3.12 has two main components. The first component at the top shows the three major statistics for the typing test: Words per minute, Accuracy, and Finger placement accuracy. Finger placement accuracy will be explained in Section **??**. The component below the statistics is a graph plotting the major statistics of the user in time. This includes when the user made the mistake and when the user slowed down, or increased their speed.

Implementation

The design will be created in Figma and the front-end will be web based.The framework the front-end will be developed in will be Svelte, due to its community resources, performance, and the researcher's familiarity with the framework. The front-end will serve as a display for the information and the interface which the user interacts and inputs information into the trainer. No calculation will be done within the front-end.

3.3.3 Back-end development of a touch typing trainer using the program created in 3.2 and the experimental setup identified in 3.1

The back-end will handle all of the computation for the trainer—mainly finger-key identification. The backend will also handle authentication and data storage.

The back-end will expose a REST API. This is a type of application programming interface (API) that conforms to the REST architectural style. One key characteristic of the this style is its statelessness and cacheable data ("What is a REST API?," n.d.). This will be implemented using Django, a Python REST API framework.

Finger-key Identification

The submodule that integrates all of the sub algorithms will be called within the framework. The framework will then respond to requests for finger-key identification using this submodule. This will allow the back-end to expose its finger-key identification abilities and allow the front-end to use this data for the trainer.

Authentication

The core authentication system will rely on JSON Web Tokens (JWTs) . According to Jones et al., 2015, "JSON Web Token (JWT) is a compact, URL-safe means of representing claims to be transferred between two parties." This allows for a user to claim that they are that specific user securely as the claim is cryptographically signed. For the backend of the trainer, the JWT will be signed using a secret and it will be encoded in HMAC SHA256.

Data Storage

The trainer will store all of the data in a relational database using PostgreSQL.This specific technology was chosen due to its maturity, community, and industry recommendations and the researchers' familiarity with the technology.

3.3.4 Testing of finger-key identification and mapping accuracy

There will be 15 videos of the researcher performing the typing test sequences. The researcher will then manually perform finger-key identification for all key presses present in the video. The finger-key identification submodule will then perform the same process for the same videos. The accuracy of the submodule will then be obtained by identifying which of its identification is incorrect, based on the manual identification.

3.4 Metric

There will be two total metrics obtained pertaining to finger and key mapping. The first will be per test sequence, and the second will be per key.

References

About TypeRacer. (2021). Retrieved October 26, 2021, from https://data.typeracer.com/misc/about

Alexanderson, S., O'Sullivan, C., & Beskow, J. (2016). Robust online motion capture labeling of finger markers. *Proceedings of the 9th International Conference on Motion in Games*, 7–13. https://doi.org/10.1145/2994258.2994264

ANSI INCITS 154-1988. (1999). *Office Machines and Supplies - Alphanumeric Machines - Keyboard Arrangement* (Standard). American National Standards Institute. Washington, D.C., USA.

Apple. (2021). How to identify your Apple keyboard layout by country or region. Retrieved October 18, 2021, from https://support.apple.com/en-ph/HT201794

Arif, A., & Stuerzlinger, W. (2009). Analysis of text entry performance metrics, 100–105. https://doi.org/10.1109/TIC-STH.2009.5444533

Baker, N., Cham, R., Cidboy, E., Cook, J., & Redfern, M. (2007). Kinematics of the fingers and hands during computer keyboard use. *Clinical Biomechanics*, *22*(1), 34–43. https://doi.org/10.1016/j.clinbiomech.2006.08.008

Baker, N., Cham, R., Hale, E., Cook, J., & Redfern, M. (2007). Digit kinematics during typing with standard and ergonomic keyboard configurations. *International Journal of Industrial Ergonomics*, *37*(4), 345–355. https://doi.org/10.1016/j.ergon.2006.12.004

Bartnik, J. (2021). https://monkeytype.com/about

Bradski, G. (2000). The OpenCV Library. *Dr. Dobb's Journal of Software Tools*.

Ciobanu, O., Gavat, C., & Cozmei, R. (2016). The keyboard remains the least economically designed computer device. https://doi.org/10.1109/EHB.2015.7391585

Common Core State Standards Initiative (CCSS). (2010). *Common core state standards for English Language Arts & Literacy in History/Social Studies, Science, and Technical Subjucts* (tech. rep.). Retrieved October 26, 2021, from http://www.corestandards.org/wp-content/uploads/ELA_Standards1.pdf

Department of Education. (2020). *Contextualized Mechanisms to guide Schools in the implementation of the Blended/Distance Learning Delivery Modality* (tech. rep.). Retrieved October 26, 2021, from https://www.depedcar.ph/sites/default/files/regionalMemos/long-memo_1.pdf

Dobson, A. (2009). *Touch Typing in Ten Hours*. Hachette UK.

Donica, D. K., Giroux, P., & Faust, A. (2018). Keyboarding instruction: Comparison of techniques for improved keyboarding skills in elementary students. *Journal of Occupational Therapy, Schools, & Early Intervention*, *11*(4), 396–410. https://doi.org/10.1080/19411243.2018.1512067

Dorfmuller-Ulhaas, K., & Schmalstieg, D. (2001). Finger tracking for interaction in augmented environments. *Proceedings IEEE and ACM International Symposium on Augmented Reality*, 55–64. https://doi.org/10.1109/ISAR.2001.970515

DraugTheWhopper. (2014). MS Natural Multimedia Keyboard. Retrieved October 28, 2021, from https://commons.wikimedia.org/wiki/File:MS_Natural_Multimedia_Keyboard.png

Ergodox EZ. (n.d.). ErgoDox EZ: An Incredible Mechanical Ergonomic Keyboard. Retrieved October 28, 2021, from https://ergodox-ez.com/

Gerr, F., Marcus, M., Ensor, C., Kleinbaum, D., Cohen, S., Edwards, A., Gentry, E., Ortiz, D., & Monteilh, C. (2002). A prospective study of computer users: I. Study design and incidence of musculoskeletal symptoms and disorders. *American Journal of Industrial Medicine*, *41*(4), 221–235. https://doi.org/10.1002/ajim.10066

Hoot, J. L. (1986). Keyboarding Instruction in the Early Grades: Must or Mistake? [Publisher: Routledge _eprint: https://doi.org/10.1080/00094056.1986.10521749]. *Childhood Education*, *63*(2), 95–101. https://doi.org/10.1080/00094056.1986.10521749

Hsu, M. H., Shih, T. K., & Chiang, J. S. (2014). Real-Time Finger Tracking for Virtual Instruments. *2014 7th International Conference on Ubi-Media Computing and Workshops*, 133–138. https://doi.org/10.1109/U-MEDIA.2014.53

Huang, T. (1996). Computer Vision : Evolution And Promise [Publisher: CERN]. https://doi.org/10.5170/CERN-1996-008.21

ISO/IEC 9995-1:2009. (2016). *Information technology — Keyboard layouts for text and office systems* (Standard). International Organization for Standardization.

Jones, M., Bradley, J., & Sakimura, N. (2015). *JSON Web Token (JWT)* (Request for Comments RFC 7519) [Num Pages: 30]. Internet Engineering Task Force. https://doi.org/10.17487/RFC7519

Keyboarding Without Tears — K-5. (2020). Retrieved October 26, 2021, from https://issuu.com/handwritingwithouttears/docs/kwtbrochure2020/1

Keybr.com - Typing lessons. (2021). Retrieved October 26, 2021, from http://www.keybr.com/

Liu, W., Anguelov, D., Erhan, D., Szegedy, C., Reed, S., Fu, C.-Y., & Berg, A. C. (2016). SSD: Single Shot MultiBox Detector [arXiv: 1512.02325]. *arXiv:1512.02325 [cs]*. https://doi.org/10.1007/978-3-319-46448-0_2

Logan, G., Ulrich, J., & Lindsey, D. (2016). Different (key)strokes for different folks: How standard and nonstandard typists balance Fitts' law and Hick's law. *Journal of Experimental Psychology: Human Perception and Performance*, *42*(12), 2084–2102. https://doi.org/10.1037/xhp0000272

Logitech C920 PRO HD Webcam, 1080p Video with Stereo Audio. (n.d.). Retrieved January 26, 2022, from https://www.logitech.com/en-ph/products/webcams/c920-pro-hd-webcam.html

Lugaresi, C., Tang, J., Nash, H., McClanahan, C., Uboweja, E., Hays, M., Zhang, F., Chang, C.-L., Yong, M., Lee, J., Chang, W.-T., Hua, W., Georg, M., & Grundmann, M. (n.d.). Hands. Retrieved January 13, 2022, from https://google.github.io/mediapipe/solutions/hands.html

Lugaresi, C., Tang, J., Nash, H., McClanahan, C., Uboweja, E., Hays, M., Zhang, F., Chang, C.-L., Yong, M., Lee, J., Chang, W.-T., Hua, W., Georg, M., & Grundmann, M. (2019). MediaPipe: A Framework for Perceiving and Processing Reality. *Third Workshop on Computer Vision for AR/VR at IEEE Computer Vision and Pattern Recognition (CVPR) 2019*. https://mixedreality.cs.cornell.edu/s/NewTitle_May1_MediaPipe_CVPR_CV4ARVR_Workshop_2019.pdf

Marklin, R. W., Simoneau, G. G., & Monroe, J. F. (1999). Wrist and forearm posture from typing on split and vertically inclined computer keyboards. *Human Factors*, *41*(4), 559–569. https://doi.org/10.1518/001872099779656770

MathWorks. (2021a). Computer Vision Toolbox. Retrieved October 28, 2021, from https://www.mathworks.com/products/computer-vision.html

MathWorks. (2021b). What Is MATLAB? Retrieved October 28, 2021, from https://www.mathworks.com/discovery/what-is-matlab.html

Matt3o. (2014). Filcom MINILA Air pictured with Logitech M705 mouse for scale. Retrieved October 28, 2021, from https://deskthority.net/wiki/File:Filco_MINILA_Air.jpg

Melville, H. (2001). *Moby Dick; Or, The Whale*. Retrieved December 7, 2021, from https://www.gutenberg.org/ebooks/2701

Norman, D. A., & Fisher, D. (1982). Why Alphabetic Keyboards Are Not Easy To Use: Keyboard Layout Doesn't Much Matter. *Human Factors*, *24*(5), 509–519. https://doi.org/10.1177/001872088202400502

OpenCV: Contours : Getting Started. (n.d.). Retrieved December 14, 2021, from https://docs.opencv.org/3.4/d4/d73/tutorial_py_contours_begin.html

Operations, V. (2021). Does Typing Cause Carpal Tunnel? 3 Myths About Carpal Tunnel Syndrome. Retrieved October 26, 2021, from https://minnesotavalleysurgerycenter.com/pain-management/does-typing-cause-carpal-tunnel-3-myths-about-carpal-tunnel-syndrome/

Parkkinen, T. (2018). The ultimate guide to keyboard layouts and form factors [Section: Keyboard Information]. Retrieved October 18, 2021, from https://blog.wooting.nl/the-ultimate-guide-to-keyboard-layouts-and-form-factors/

Poole, D., & Preciado, M. (2016). Touch typing instruction: Elementary teachers' beliefs and practices. *Computers and Education*, *102*, 1–14. https://doi.org/10.1016/j.compedu.2016.06.008

Ripat, J., Giesbrecht, E., Quanbury, A., & Kelso, S. (2010). Effectiveness of an ergonomic keyboard for typists with work related upper extremity disorders: A follow-up study. *Work*, *37*(3), 275–283. https://doi.org/10.3233/WOR-2010-1079

Rumudiez. (2013). Correctly labeled modifier keys for the ANSI Keyboard layout. Retrieved October 18, 2021, from https://commons.wikimedia.org/wiki/File:ANSI_Keyboard_Layout_Diagram_with_Form_Factor.svg

Serina, E. R., Tal, R., & Rempel, D. (1999). Wrist and forearm postures and motions during typing. *Ergonomics*, *42*(7), 938–951. https://doi.org/10.1080/001401399185225

Sobel, I. (2014). An Isotropic 3x3 Image Gradient Operator. *Presentation at Stanford A.I. Project 1968*.

Suzuki, S., & Abe, K. (1985). Topological structural analysis of digitized binary images by border following. *Computer Vision, Graphics, and Image Processing*, *30*(1), 32–46. https://doi.org/10.1016/0734-189X(85)90016-7

Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V., & Rabinovich, A. (2015). Going deeper with convolutions [ISSN: 1063-6919], *07-12-June-2015*, 1–9. https://doi.org/10.1109/CVPR.2015.7298594

Szeto, G., Straker, L., & O'Sullivan, P. (2005). A comparison of symptomatic and asymptomatic office workers performing monotonous keyboard work - 2: Neck and shoulder kinematics. *Manual Therapy*, *10*(4), 281–291. https://doi.org/10.1016/j.math.2005.01.005

Toosi, K. K., Hogaboom, N. S., Oyster, M. L., & Boninger, M. L. (2015). Computer keyboarding biomechanics and acute changes in median nerve indicative of carpal tunnel syndrome. *Clinical Biomechanics*, *30*(6), 546–550. https://doi.org/10.1016/j.clinbiomech.2015.04.008

UMass Amherst. (n.d.). An Overview of Quizzes in Moodle — UMass Amherst Information Technology — UMass Amherst. Retrieved October 26, 2021, from https://www.umass.edu/it/support/moodle/overview-quizzes-moodle

What is a REST API? (n.d.). Retrieved January 26, 2022, from https://www.redhat.com/en/topics/api/what-is-a-rest-api

Wheatland, N., Wang, Y., Song, H., Neff, M., Zordan, V., & Jörg, S. (2015). State of the Art in Hand and Finger Modeling and Animation. *Computer Graphics Forum*, *34*(2), 735–760. https://doi.org/10.1111/cgf.12595

Yousaf, M., & Habib, H. (2014). Virtual Keyboard: Real-Time Finger Joints Tracking for Keystroke Detection and Recognition. *Arabian Journal for Science and Engineering*, *39*(2), 923–934. https://doi.org/10.1007/s13369-013-0909-2