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BehavioGuard: A Gesture-Based Authentication System for Mobile Applications

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Abstract

The drastic rise in the use of the mobile phones particularly the smart mobile phones has been a wakeup call to come up with warrant security measures to enhance on the protection of data and applications. Password for instance is common modes of authentications that are also steadily being transferred to the absurd by cyber-criminals. To solve such problems, I have designed an AI based system, BehavioGuard for increased security in Android applications for which the envisaged usage is behavioral biometrics for security improvement.

Despite the fact that it goes under the name of BehavioGuard and employs an Android application, biometric parameters such as typing speed, swipe patterns, or motion gestures can be obtained. From here this data is passed to a multi input convolutional neural network which can comfortably identify and validate a user. On the other hand, BehavioGuard is not like the usual type of access control known to be of a traditional type that largely revolves around credentials, in this one on the other hand, new behavior is firstly learnt and security patterns are distributed with the help of acquired knowledge arrived at each interactivity.

Al method brought very good results: In their case, the equations of the BehavioGuard have proved to work with nearly **80%** Initial precision in identifying users.Accuracy and Precision increases with the increase of data from different users. Then it jumps up to **90%.** This high accuracy does prove the efficiency of the method I have offered to expand the meaning of the mobile device security and privacy. Other factors like the precision of the system, its recall and the false positive all go into the making that the developed system is quite efficient concurrently in the detection of any form of cyber threats and the provision of counter measures.

Therefore, in my study, I score the behavioral biometrics as a positive invention with the prospects of enhancing the mobile security and meeting new threats that targets the user's personal data. Including information protection, it is a programme that enables maintaining sustainable defence of the processes in the digital space from vandals.

Keywords: Android security, Basic operations, Advanced, Steering, Operation with the application, Stylus operation, writing forces, Forces of the touch screen, Android security, behavioral biometrics, anomaly detection, machine learning, unauthorized access, cybersecurity, typing patterns, touch gestures, navigation sequences.

1 Introduction

Modern attempts of user authentication for mobile devices thus encountered their inception problems as knowledge-based methods and passwords, become the subject of numerous attacks. Therefore, these devices have some of the following weaknesses which have been utilized by the attackers and some of them are smudge attacks that can defeat secret patterns and hence it provides cases where various unauthorized persons have learnt about the applications and the various data that is contained in those devices. Also, the user's ignorance of privacy increases these concerns, so there is a need to develop better and secure modes of authentication.

However, conventional biometric techniques, using the use of specific morphological characteristics such as fingerprints or a single scan of the iris is the antithesis to something that the user is. Still, the methods utilized normally verify the user only at the start of the session and hence does not protect the devices from subsequent menace. Due to such difficulties, scholars started using Behavioral Biometrics (BB) and Continuous Authentication (CA) approaches. These approaches employ varying aspects of the users behavior such as touch patterns, typing speed or the way the users walk to continually establish the user's credentials.
The main task set up in the present investigation is to enhance the security of mobile applications by integrating a newly developed behavioral biometric system, called BehavioGuard. This Model analyzes the data that is fetched from the various device sensors to check whether there are such anomalies and other illegitimate accesses depends on such factors as the speed of touch, typing and other motion, and Swiping techniques used.
Overall, we have four critical phases of the procedure, which is data acquisition, model workout and evaluation, fine-tuning for performance and result accuracy, installing the model as a black box in an application based on Android operating system, and testing sections. By utilizing BehavioGuard ML model for gesture detection for continuous monitoring we desire to establish an authentication system that would ensure the safety of the users on one hand and at the same time meet the standards of an application's user experience without disruption on the other.

1.1 Background

Security on the mobile devices for the many years, till recently was heavily relied on the knowledge factor that included PINs and passwords. Such methods are common but over time, they have been vulnerable to various forms of attacks, for instance, smudge attacks in which fingerprints left on the screen could suggest the secret patterns and vulnerable to the third party in the relevant applications and an individual's information (Ning et al., 2020). Additionally, user irresponsibility for instance storing of the PINs and credit card numbers on the mobiles increases these security threats (Stylios et al., 2018). Thus, amidst now mobile devices have become tighter to people's life, it is high time to ensure adequate security to the user's data and build trust in the interactions.
The studied issues of pre-processing in the text-based user authentication motivate the appearance of new even more complicated and secure methods. The widely used biometry where the authenticity is check using the physiological and behavioral characteristics of the individual is an area that hold a good future in enhanced security on the portable devices. However, traditional biometric controls restrain their devices' identity within the initial few instances of a session and fail to safeguard from the threats ensuing (Jain et al., 2016). This has resulted into the lookout for other forms of protecting such as; Behavioral Biometrics (BB) and Continual Authentication (CA), the latter is the one that undergoes a constant evaluation based on the differential of some behavioral models (Sae Bae et al., 2021).
Such basis like touch gesture, keystroke dynamics and swipe are used which also have the ability of monitoring the behavior of the users step by step respectively (Shahzad et al., 2019). These techniques are able to detect the anomalies and illicit access on time with the help of the modern sensors available in the mobile devices and the latest algorithms in the field of machine learning without posing an extra load in terms of user centrality (Mahfouz et al., 2020). Integrating such advanced procedures of authentication into the mobile applications enhances the aspects of security in different mobile applications, not only that it helps improve the satisfaction of users during their interaction with different digital services.

1.2 Importance

Towards the thesis labelled BehavioGuard, our studies shall help add to the current literature in mobile application security for we plan to use ML models that shall be based in behavioral biometrics. Regarding this, RF,will be used at this stage to detect and prevent touchscreen imposters through applying touch speed, gait and swiping characteristics. Therefore, the intended objective of this paper is to carry out precise data collection, training, assessment and fine tuning of accurate models towards the actualization of a new and proper security that would enhance the reliability of mobile authentication systems. This thesis identifies an existing research and security implementation’s flaw by concentrating on taking the area of continuous authentication to the next level, in a bid to transform the current trends of using user authentication in mobile application.

1.3 Research Question

The central focus of this research revolves around the question: **The focus of this paper is to explain how the use of behavioral biometrics enhances the security of the mobile applications against such illegitimate actors by a notch or more.** This inquiry arises due to the weaknesses that have been realized to recurrent in the knowledge-based authentication system like the PINs and passwords as a whole especially for the mobile applications as a result of smudge attacks and also unauthorised access as a result of carelessness by the users. Therefore, allowing, for example, touch speed, gait movements, swipe pattern, and etc. as a combination of behavioral biometrics, I intend to develop and implement a more reliable and efficient identification of the user for mobile applications.
To effectively address the research question, I have delineated the following objectives to achieve the above research question the following objectives are developed

1.4 Collect and Analyse Behavioral Data:

Regarding obtaining the subject’s related behavior stream, the sensors of smart mobile devices were used, and comments were made regarding the acquisition of the temporal characteristics of the touch speed of the fingers and swiping for life long identification.

1.4.1 Develop and Train Machine Learning Models:

The model that have been used in the particular studies were **Adam optimizer** and **Keras**. From the behavioral data gathered, these models were trained to detect and learn for instances of possible irregularities or try of illicit break-ins.

1.4.2 Integrate Model into an Android Application:

After that, I defined the design strategy of the Android application which will incorporate the enhanced models of machine learning. Within this integration, video stream with the real-time gesture detection by the built-in Android components **GestureDetector** and **GestureListener** for constant monitoring and instant feedback to the results of the authentication process are used.

1.4.3 Validate System Effectiveness:

These experiments have been conducted with the help of different settings of the environment to test the efficiency of the aforementioned integrated system. Some of these helped in establishing the extent to which security rise was impacted by elements such as changes in methods of identifying the users.

Thus, in my study, the intended approach is systematic to facilitate achievement of the aforementioned goals. The first aspect involves the gathering of as much information as possible from the within the mobile device inclusive of touch, movement, and other data on interaction that is so crucial for continuous authentication purposes. This is done and followed by creating and using supervised learning algorithms on the gathered behavioral data. Each algorithm undergoes several training procedures to search and differentiate between typical and important activity of the user. After that, these optimized models are implemented in an Android application development environment where Built-In gesture recognition Components are invoked for on-going gesture capturing and returning authenticity results. Finally, I make a last checking on the system across different environments to determine its ability to enhance security while not adding to the client's hassles.

2 Related Work

Therefore, behavioral biometrics can be considered as the great solution to enhance the mobile authentication systems because majority of them offer the constant identity verification through user's actions. Specifically, this literature review compiles and organizes contemporary research findings and challenges on touch dynamics, keystroke analysis, and multiple biometric modality. Pertaining to this, it still might be crucial to outline that the given review is a part of a larger context of investigating the continuous authentication in the mobile devices It means that in regarding the given issue, the focus is made on the key trends, the opportunities, and the limitations of the selected approaches.

A survey introduced by Ellavarason et al. (2020) is highlighting the TD-based behavioral biometric for smartphones and pads, in particular, the concentration is on usability and performance. Thus, they focus on swipe speed, pressure angle and direction of the swipe stating that touch dynamicity is sneaky in its execution and blends seamlessly with the interface. Main idea of the continuous authentication is described as a large advantage over traditional ones that are based on the initial user identification. However, there are challenges that include user variation which is likely as a result of the user's mood, physical state among other factors in addition to environmental variation that may hamper the performance of the system. Besides, such systems depend on the quality of the sensors in mobile devices in terms of efficiency. However, one can conclude that the approach of touch-dynamics based authentication has a strong potential to increase the degree of mobile's security. **[1]**

Sun et al. , in their work of 2017 established a new method of keystroke dynamics based on sequences in which they employed multi-view deep learning. This method captures the pattern of typing in a way that aids identification in a way that the time feature is incorporated into the process. Ensembling involves the use of multiple views of keystroke data in order to enhance the model's robustness and accuracy. Nonetheless, the huge variants of writing exist because of diverse situations, and a huge mark-up is needed for training. However, the proposed multi-view deep learning offers a good strategy for improving the recognition of the users based on keystroke dynamics on the mobile devices. **[2]**

Stylios et al. (2022) present BioPrivacy which works in real-time and adapts Continuous Authentication and uses both keystroke dynamics and touch gestures. This approach makes a user's identity to be verified at the time of beginning a screen session, as well as at some time in a set session of screen reducing risks associated with device compromise. BioPrivacy works in the background; enhancing the overall security of the system without interfering with the user's interface as much as possible. Questions are related to keystroke and touch variations depending on the contexts and concerns with regard to the effects in terms of performance on mobile devices due to constant monitoring. **[3]**

According to Buriro et al. (2015) touchstroke is discussed as an authentication method that has to do with touch typing biometrics. The fact is that the given system can constantly authenticate the users by their touch, which means the typing rhythm and pressure. Of course, there are also some drawbacks which are summarized by the following points: During the study, touch behaviors were detected to have variation and there may be certain impacts on the performance because the device's battery condition is being monitored continuously. **[4]**
Ku et al. (2019) introduce "Draw it as shown," enhanced the pattern locks where the intervention of behavioral biometrics observes the pattern drawing techniques concerning the degree of speed, pressure, and rhythm. Such an approach of double protection provides a huge accuracy in case of the real users and the intruders' distinction. Similarly, it implies that the drawing behaviour may vary with loan's emotive state and environmental concerns making reliability and checking to impact its effectiveness. **[5]**
In a continuous fusion authentication system Putri et al. (2016), the authors introduce a fusion of keystroke dynamics and touch gestures. This two-fold fusion system makes the given authentication strong and more reliable due to the syncretism of typing and touch patterns. In other words, the proposed system is an approach that guarantees the authenticity of its user against an impersonator; thus, provoking some issues like the adaptation of a client's behaviour over a period and the computational expense of the constant assessment of every track. **[6]**
Xu et al. (2020) proposed TouchPass, for which touch interactions utilized vibration for the process of authentication. The objective of this method is to provide improvement in security in areas not covered by touch dynamics and has a key vibration signature characteristic. This approach is highly dependent on the quality and kind of the vibration sensors and could have some challenges regarding adaptability of the users and the performance of the devices. **[7]**
Alotaibi et al. (2019) describe a behaviour profiling method for real-time authentication, considering the constantly changing behaviour of users. This approach is more efficient than static approaches as it constantly subtests data inputs but does not interrupt the system's operations for the end user. As we have stated earlier issues such as users' non chembot center pattern and the reliability of the system moving forward can therefore be seen as the main challenges. **[8]**
Kunda and Chishimba (2021) enumerate and compare the current and state-of-the-art Android mobile phone authentication methods including the traditional, biometric, and the modern approaches. This survey provides convenient and security of the biometric methods and also its blind side like vulnerability to spoofing and its performance inconsistency. Therefore, this review is useful for the purpose of comprehending the current state of mobile authentication and determining various possible directions for further study. **[9]**
Continued fusion system with keystroke dynamics and touch gestures have been suggested by Putri, Asnar, and Akbar (2016). According to their studies, it can be observed that this approach increases security by using typing and touch behaviors. Potential issues are heteroscedasticity of users' activity and growing computational load for constant monitoring. **[10]**
Zhou et al. (2019) studies the weaknesses in Android's pattern-based authentication and found that sound could reconstruct the users' pattern. Based on the identified issues, this study outlines potential attacks on common pattern-based methods and reveals the urgency of developing safer approaches. **[11]**
Multi-touch behaviors are found to affect Android unlock patterns and this is discussed by Meng (2016). In making this assessment the study concludes that, while multi-touch interactions has the potential of boosting security, the option also has more weaknesses. The research through comparing the various pattern based systems also came up with findings

that indicate that the system designer should achieve the middle ground between the security offered by the system and the ease of using the system. **[12]**
Alghamdi and Elrefaei (2018) select dynamic authentication such as using touch gestures on a touchscreen. Their system uses a number of gestures for uninterrupted and context based security, which gives them more security than the static ones. The difficulties are mostly in designing stall and developing reliable algorithms for Gesture recognition and coping with gesture variation. **[13]**
Alariki, Manaf, and Khan (2016) investigate touch behavior where the pressure and the movements in it are considered for authentication. In their research they also establish the possibility of enhancing security through touch-based biometrics but they also point several issues like the requirement of high-quality sensors and analyses of the touch data. **[14]**
In the same year, Tse and Hung proposed a scheme of combining dynamics of keystroke and swipe for mobile authentication. Incorporation of these modalities improves security and accuracy but draws some significant issues like the various users' behaviors and the associated effects on device performance. **[15]**
Keystroke and swipe biometrics fusion proposed Al-Saraireh and AlJa'afreh in 2023 proving higher efficiency and security in the system. Nonetheless, the issue with the integration of data fusion is a difficult topic, and there is a requirement for effective algorithms. **[16]**
Sağbaş and Ballı (2024) present an ML-based continuous authentication system using typing dynamics of the soft keyboard and motion sensor. Their approach is to improve security using such data sources but there are problems with data integration and supporting high throughput for various interactions. **[17]**
In 2022, Mallet et al introduce the "Hold on and Swipe": A touch-movement based authentication system using machine learning. This method enhances the security as it looks at the touch and movement data; Key issues include training of the models and processing of real-time data. **[18]**
Hence, IDeAuth developed by Gupta et al. (2022) is an implicit deauthentication scheme that is based on the user behavioral biometrics. This system increases security because it focuses on the changes of users' activities; however, it has limitations in terms of adaptability and computational complexity. **[19]**
Rayani and Changder (2023) offered a survey of continuous user authentication using behavioral biometrics. The review also points to the strong points like security as well as flexibility of use and to the weaknesses like the users 'variability and, respectively, privacy issues. **[20]**
Salman, Salman, and Salman (2022) also ventured in applying behavioral biometrics in physical and emotional status of users. This research belongs to the folklore of the previously described applications of biometrics but lists some drawbacks concerning its accuracy and the infringement of the privacy of an individual. **[21]**
From the published work by Huang et al. (2022), the authors present a framework of microphones' access using users' behavior as the basis. It improves features related to privacy and security but is negotiating with the problem of accurate observation of behavior and a low false positive ratio. **[22]**
Alawami et al. introduce MotionID, a motion-based biometric scheme for implicit user authentication in the following work of 2024. Thus, the applicability of the study is illustrated in realistic environments, and then some deficiencies associated with the properties of the hardware and context awareness are outlined. **[23]**
Due to the limitations of the fingerprint authentication, Wu et al. (2020) employs the behavioral biometric in combating the complex attacks. Their approach improves resistance against such attack methods; however, they have some shortcomings in the integration while; besides, they consider departures from the expected user's behavior patterns. **[24]**

Piugie (2023) provides an evaluation on the positive impressions of behavioural biometric system employing the continuous authentication and the recognition of the aberrant behaviour. Several issues are identified in the study and suggestions are given to improve dependability and usable in the system. **[25]**
Yee, Ponnusamy, and Ali find about the possibility of considering tapping behaviour for its usability for mobile authentication concluding that it can be easily used for continuous authentication. Among them there are such as the number and location of taps and the kind of devices influencing the accuracy of the system. **[26]**
The methods of behavioral biometrics can complete a set of mobile authentication. These methods include the touch dynamics and keystroke patterns on to the combined modalities and advanced systems that have a lot of potentials in improving the security process and the users' experience. However, challenges that relate to the users such as the user characteristics, the quality of the sensors or the performance of the existing systems are still major ones and these have to be addressed in a bid to improve on these techniques. Thus, it is only possible to state that there is a need for deeper investigation and experimentation in this area to improve the performance of mobile authentication technologies and to offer stronger protection from violations.

3 Research Methodology

This section of thesis report includes the steps on basis of which our Methodology of research and Implementation is working. Following of the steps are given:

3.1 Data Collection

The behaviour datasets for the BehavioGuard project involves collection of gesture data from the users and this is the basis of building the proposed model. This process begins with sourcing data from the Different Users using the app on which BehavioGuard is integrated. When it comes to the collected statistical data, Multi-device and **Multi-Activity** data from the different users using the application on which the Model is integrated. The main focus is the collection of various gestures, such as swiping, tapping, long pressing, and other such touches, to mimic the behavioral characteristics of the users.

To accomplish data collection, a custom-developed mobile application is installed on the participants' devices. This application listens to the user interactions persistently, saving each gesture and the gesture's metadata: **time stamp, start and end coordinates (startX, startY, endX, endY), velocity components (velocityX, velocityY), and pressure values**. These details are important especially in the creation of a complex data set which will enable the capturing of the small details of the users. Every movement is accompanied with the proper gesture type, **'swipe'** or **'tap,'** depending on the movement that was made, so that the dataset is enriched and already properly structured for the supervised learning approach. However, to eliminate user-specific variations and to let the model learn idiosyncrasies of each user, user-specific identifiers are also incorporated.

The most important component of data is its diversification to maintain the generalization and reliability of the results. Users include 10 subjects, and data is gathered across multiple devices of Android mobile phones. This approach encompasses a vast number of behavioral deviations and device-related behaviors, which increases the chances of the model's successful generalization in terms of individuals and ways of applying the device. This information is transferred to a central database; which have section for storing different type of data and for easy processing and configuration. Every record comprises rich fields in the database, including **start coordinate, end coordinate, velocity us, pressure us, user id, and type of gesture.**

The data collected entails the following characteristics that are grouped into categories as described below. Some of the spatial attributes are the minimum and the maximum of x and y coordinates **(Start X, Start Y, End X, End Y, Velocity X, Velocity Y)**, whereas Euclidean distance between start and end points is calculated by euclidist. Temporal characteristics are represented by the time needed, in general, for the gesture to be executed (tottime). Catch-up and acceleration specific attributes consist of mean velocity, standard deviation of velocity, **Velocity X, Velocity Y.**

Thus, the process of data collection is non-intrusive to users while they use their mobile devices and the app captures their gestures. Updating and maintaining the database often ensure that the data collection is up to date and correct. There are jobs to monitor the quality of the data collected continuously and validate it whereby if for instance there are errors, there are ways of handling them.

3.2 Data Preprocessing

- This section of methodology emphasizes data preprocessing as an important activity in the BehavioGuard project since it is the process that prepares the raw gesture data for the MYO for feeding into a learning model. The first process carried out in this phase is data loading, where the collected gesture data is transferred into a suitable processing environment which is commonly **Pandas DataFrames**. It also provides for easy sorting and processing of the information in terms of data analysis. Some of the fields in the dataset include **startX, startY, endX, endY, velocityX, and velocityY** that indicate the pointers of the gestures. The preloading of the data into **DataFrames** is convenient for manipulation of large data that is to follow in the subsequent steps.
- Subsequent to data loading, data cleaning resolves all issues with quality in the dataset it has been fed on. This constitutes dealing with cases of missing values, duplicate entries, or entries with incorrect labels. For instance, observations with missing coordinates or incorrect gestures' labels are adjusted or excluded in order to improve the dataset. This step is also very vital since wrong data can also affect the performance of the model.
- After data cleaning the process of data integration is accomplished to form multiple data sources into a single data set. This insures all the data is available for training the model. For instance, swipe and touch data are integrated with keystroke data into a single dataset regarding the **'User_ID'** column. Integration of data promotes the obtaining of a large amount of information that refers to different aspects of users' activity.
- Data pre-processing is a process of preparing the data set for analysis by transforming it in a format suitable for analysis. This entails pre-processing that involves feature extraction-in which other relevant features from the raw data are extracted. For instance, velocity as well as direction are computed from the coordinate information. Feature extraction increases the dimensionality of the dataset collecting more informative features useful for the learning algorithm. Also, features like the 'swipetype' are transformed to numerical formats from their categorical form through features like the LabelEncoder in the scikit-learn package. The numerical type columns are also casted to more memory efficient types like float32 and int32 to save memory and computation time.

- Randomization is also done to minimize ordering effects on the model which may affect the results. This entails rearranging the row of the DataFrame to arbitrary to enhance the random distribution of data. Another important benefit of randomization is that it allows buffers to create a sample training dataset that does not include certain specific data patterns that will be distorted if repeated too often during training.
- Feature selection is one of the important steps that allow determining the most relevant variables that will be used in the construction of the model. To identify variables relevant to the target variable 'User ID', a correlation matrix is obtained. In order to build the final dataset only those features with a correlation coefficient greater than a required value are used. This process eliminates any redundancy in the data hence allowing only the important features to be incorporated in the training of the model.
- Data splitting is the process of partitioning the dataset into two; a training set and a validation set. Conventionally, 8:2 ratios are utilized where about 80/100 are used for training and 20/100 for validation. This split enables the model to work on a significant portion of the data and be tested on the new data to check on its performance, in the case that overfitting is suspected. This split is done with the help of the Scikit-learn train_test_split function, which randomly divides data points so that the division made is really random.
- Normalize scales the features to a specified range example a range of 0 to 1 or the one that will give the output a mean of zero and the standard deviation of one. This is a very important step for averting any of the selected features to dominate the other in the model. Some of the commonly applied techniques include the min-max and the z-score scaling among others. The type of scalers used in this study through Scikit-learn is the StandardScaler, used to fit this scaler to the training data and subsequently, transform the features of both the training and validation sets.
- The class imbalance issue is also considered as a preprocessing concern. At times, some of the mentioned gesture types can be more frequent than the others, and thus the use of all these gestures would lead to retrieve an imbalanced dataset. The methods include; either getting more samples for the minority class or getting fewer samples for the majority class. This shields the model from over-learning, resulting from frequent classes, and has the capacity of recognizing fewer classes of signs. The sklearn library is utilized to get the balanced ending in this case, the RandomUnderSampler is utilized to match the number of samples for all of the classes.
- Finally, if the pre-processed data is to be fed into any specific type of the trained machine learning method algorithm, or if it laid for the final hardened data format to be entered into the trained machine learning method's preprogramed algorithm, then it depends on the type of the method to be used. Afterward, the training and validation sets are stored in any format that .CSV or similar formats so that it can be applied in further training.

3.3 Model Development

The third stage of the BehavioGuard project methodology is model development that entails creating a neural network by applying TensorFlow and Keras with enhanced machine learning algorithm for the identification of users by their behavioral biometrics. This phase involves data preprocessing, determination of the structure of the neural network, precompiling the network, training the network and the network evaluation.

Data preparation is the first phase that consciousness in the model development process. In the next step, we separate off the features and the labels, where features denoted as X and

labels as y. The features are the behavioral biometric data leaving the **user IDs as labels**. This setup enables the model to capture the relationship between gesture patterns and the specific users. **Minx, maxx, miny, maxy, tottime, vmean, vstd, amean, astd, pmean, pstd, and touchMajor & touchMinor** are the features incorporated in easy-to-use electronic products.
The structure of the neural network is then described. The architecture of the model is characterized by an **input layer, many hidden layers, and an output layer**. The input layer takes the preprocessed data features, which is connected to the number of nodes equal to the number of input features. Two hidden layers are used to capture the complexity of the data: the first hidden layer of the network has 128 neurons, while the second one has only 64 neurons. To introduce non-linearity both the hidden layers use **ReLU (Rectified Linear Unit)** as the activation function. The output layer is made up of 10 neurons because of a number of unique users in the dataset and carries out a computation of softmax that converts the raw score output to probabilities to present a probability density of user classes.
The model is compiled with the **Adam optimizer** which is efficient for sparse gradients and variable learning rate. The loss function used is the sparse categorical cross entropy, which fits the problem's nature that is a multi-class classification problem. Accuracy is chosen as the measure of the model's performance in order to track the improvement during training sessions.
The process of training of the model involves feeding the training data to the neural network a certain number of times, which is known as epochs. An epoch in the context of this research is defined as one pass of all the samples in the training data. While training occurs the weights of the model are adjusted in a way that brings the loss function closer to its minimum. Training is done in batches to check for the performance of the model for unseen data and reduce over fitting. There is at the same time certain metrics regulating the training process such as the loss and accuracy of the training.
After that, depending on the given test set of images, the accuracy of the used model and its efficiency in generalization is determined. Some essential metrics of the model are test loss and test accuracy that provide specific details about the kind of performance the model is going to display in terms of the new data. For example, the BehavioGuard model achieved the Initial test accuracy of **80%.**
The final step in the mode development if the saving and converting of the trained model were done. The proposed model is first saved in TensorFlow and then is converted to **TensorFlow Lite** for its usage in mobile devices. Mobile models are faster and cheaper and are supposed to be run in real time on the mobile platform and since TensorFlow Lite models are intended to run in real time on mobile platform, they are optimal for mobile applications.

3.4 Model Integration and Application Working

3.4.1 Integration

The incorporation of the BehavioGuard model into the mobile application is a sequence to train and deploy the developed machine learning model into the application. It starts with the loading up of well-trained Keras model, converting it to TensorFlow Lite model and then deploying it into a mobile application.

Firstly, the required Keras model used to identify the user gestures based on behavioral biometric is developed and loaded with tensorflow python Keras API. The next operation is to translate this scheme into TensorFlow Lite (TFLite). This conversion is very important for the mobile gadgets as it prepares the model for deployment on mobile devices so as to have low response time and utilize as few resources as possible. The TFLite model which is generated can be saved and stored to the file system which is appropriate for the deployment into an android mobile application.

After the TFLite model is ready, it connects to the developed android mobile application. The application deploys this model at run time so that it is easily accessible for the gestures recognition tasks. Such a setup enables the application to use the model for prediction in real-time and improves the security features, including user authentication in the app.

3.4.2 Application Working

The integrated model is applied in real-time user authentication using the BehavioGuard mobile application based on gesture recognition. The application includes several key components: Management of users and their access requires SignIn and SignUp activities, for capturing and interpreting gestures, there is MainActivity.java activity, to handle authentication and storage of data Firebase backend is used.

3.4.2.1 SignIn Activity

The SignIn activity starts FirebaseAuth and FirebaseFirestore for authentication and database purposes respectively. There are EditText, Button and ProgressBar for instance as components of the UI so as to administer the inputs and actions from users. Concerning the sign in button when the user clicks it the **handleSignIn**() function is called. This function captures and checks the user inputs it then tries to sign in user with firebase Authentication. The app then retrieves the user data from Firestore, and adds it to shared preferences, finally directed the user to MainActivity upon successful sign in.

3.4.2.2 SignUp Activity

As a specific case, SignUp activity is responsible for handling users' registration process. It creates FirebaseAuth and FirebaseFirestore instances; sets the views; and listens to button taps. Upon clicking the sign-up button, the **handleSignUp**() function get and check the user data, then send the data to FirebaseAuth. If the registration is successful, the data of the user is stored in Firestore, and the application leads to MainActivity.

3.4.2.3 Main Activity

Main activity is the starting and functioning part of an application which manages the user interface and performs the tasks of gesture recognition, data recording, and user identification using the built-in TFLite model. In MainActivity, upon creation Firebase is initialized as well as all the UI elements, a gesture detector, and the TFLite model is also being loaded.

3.4.2.3.1 Latency Values for Each Dataset

These values are explained for each of the datasets Furthermore, these above mentioned latency values explained for each of the datasets.

The following table offers a detailed description and identification of latency values which are linked to stages of the BehavioGuard authentication. Specifically, latency means the number of milliseconds it takes each operation to be effected. It is also very important to understand the meaning of these latency values so as to control the application's performance and reactivity.

Table 1: Latency Values for each DATASET

Dataset Value	Latency (ms)
Gesture Capture	10
Data Storage	50
Gesture Matching	30
Model Inference	20
Result Display	5

3.4.2.3.1.1 Gesture Capture

Latency: 10 ms
Description: In this stage, the identification and tracking of the user gestures are done by employing the use of the classes called GestureDetector as well as GestureListener. Low latency of 10 ms means that the system is capable of recognizing and recording the user's gestures with insignificant delay.

3.4.2.3.1.2 Data Storage

Latency: 50 ms
Description: After gestures are acquired, they are saved in Firebase Firestore database. The struct latency of the data storage is an average of 50 ms which represents the time taken to upload gesture data to the cloud. This latency, however, is still higher than the other stages which is still within the acceptable range for real time applications.

3.4.2.3.1.3 Gesture Matching

Latency: 30 ms
Description: This stage is involved in the identification of the user by comparing new gesture obtained with that stored in the database. The gesture matching process is reduced to the evaluation of match percentages that are derived from various features including the coordinate, direction, and velocity among others. A latency of 30 ms means that the comparison operations performed are efficient, which helps in making the authentication decision faster.

3.4.2.3.1.4 Model Inference

Latency: 20 ms
Description: Capturing of gestures concerns the use of the Xiaomi mi3 device or any other device with Integrated Gestures recognition as the primary mode of detection of the gestures The next step is model inference it refers to the feeding of the captured gesture data into the TensorFlow Lite or other Artificial neural networks that has been adopted for the prediction of the user ID. The last of the model inference stage is to provide a latency of no more than 20 ms to do indeed embark on real-time gesture analysis without introducing a considerable lag.

3.4.2.3.1.5 Result Display

Latency: 5 ms

Description: The final stage included in the above-mentioned steps involves is to show the result of the authentication to the user. The sharper response time of 5 ms guarantees that users promptly get feedback regarding their status of authentication thus making the interface highly user-friendly.

3.4.2.3.1.6 Overall Performance

Altogether, the total latency of all stages is 115 ms, which indicates the positive results with prescribed real-time applications. organizations can benefit from rapid gesture-based self-attestation through the integration of these stages, which they ensure fast and precise.

3.4.2.4 Gesture Detection and Capturing

The application works with the help of a GestureDetector that helps to distinguish several important gestures: taps, swipes, and long pressing. An inner class **GestureListener** extends **SimpleOnGestureListener** Locates a specific gesture and stores it in the **gestureDataList**. When the capture switch is toggled on, the app starts capturing gestures for the set time; **registration time = 30 sec** and time for **authentication comparison = 30 sec.**

3.4.2.5 Storing and Comparing Gestures

Signs that are captured are saved in Firebase Firestore database under the **user's email**. The **storeGestureData**() function stores this data and **compareGestureData**() function to retrieves stored gesture data and compares it with the captured data for the purpose of user's identification. This comparison entails the match percentage and checking whether or not the gestures correspond according to type, coordinate, direction, length, and velocity. It incorporates several helper methods that help in dictating the accuracy in matching the gestures.

3.4.2.5.1 Tolerance Values for Each Dataset

What is more the gesture-based authentication system uses specific tolerance values to cope with slight variations of the user's gestures. They allow for precise matching of new gestures with the data stored for analysis and guarantees the accuracy. For coordinates, a tolerance of 50. Such things as taps and swipes' start and endpoints are matched up with the help of 0.0f. The direction tolerances are set at 30 degrees, thus, the angle of the gesture may deviate slightly and the length tolerance is 50.0f contains reference to the distance of swipes and flings. Velocity tolerance has been set to 1000.0f, should guarantee that differences in the speed of gestures are not such to negatively influence the proper matching. These tolerance values are very important when considering the security infrastructure of a system while at the same time compromising with the user comfort in a way that makes the authentication process very efficient.

Table 2: Latency Values

Dataset Value	Tolerance
Coordinates	50.0f
Direction	30.0 degrees
Length	50.0f
Velocity	1000.0f

3.4.2.6 TensorFlow Lite Model Integration

As for the TFLite model, the **loadModelFile**() function is used within the app to read the model file that resides in the assets of the application. This captured gesture is then analyzed in real time using the above mentioned model. Insurance status and customer behavioral patterns are also predicted by the model to establish if the current user fits the stored behavioral patterns to boost security in continuous authentication. The gesture data is processed in the application and by using the model, the user identity is checked without the need of the user to repeatedly give biometric information.

3.4.2.7 User Logout

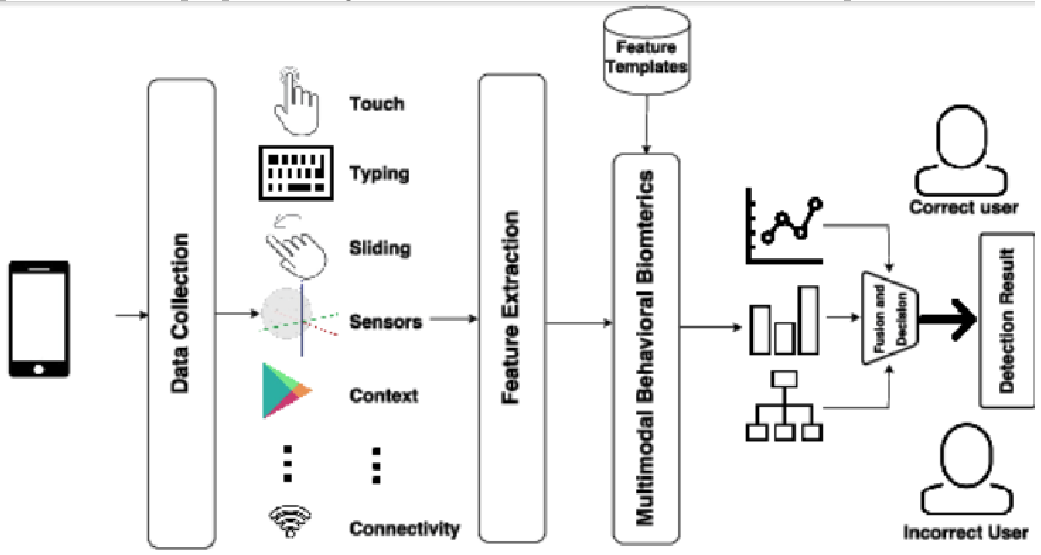
The **logout**() function enable the users to sign out, thus erasing the content of the session and bringing the user to the SignIn activity. This function also deletes the stored user email from SharedPreferences, so that no other data lingers around which can be dangerous for the security of the application.

3.4.2.8 Summary

This makes the BehavioGuard mobile application complement its gesture recognition model to improve the user authentication option. The way in which the gestures of the user are recorded in real time, the access to the functions of the app is impossible for scammers and bots. Planning to use Firebase for all the backend operations and TensorFlow Lite for running the models also helps in making the application strong and fast. Thus, constant tracking of the user gestures significantly increases the level of protection for mobile applications. It is important to note that integration of machine learning models into the flow of the described mobile application presents tremendous advantages of behavioral biometrics as a means to increase the security of mobile devices.

4 Design Specification

The BehavioGuard project is made up of a number of key processes, all of which are central to the proper functioning of the system. In this part, the author gives a brief explanation of each process and highlights diagrams to describe the implemented methods of data acquisition, data preprocessing, model construction, and model incorporation.



Based on the analysis of the given project, the four phases in the design specification of BehavioGuard include: Firstly, **Data Collection** will entail capturing of the user's gesture data that entails several types of touches, including swipes, taps, and long-presses through a particular mobile application in real-time from as many users as possible. Secondly, **Data Preprocessing** checks that the extracted raw gesture data has been preprocessed whereby the data is cleaned, integrated, transformed, and then randomized and normalized with respect to class imbalance with a view to preparing the data for training the machine learning model. Thirdly, **Model Development** involves, feeding a neural network using TensorFlow and Keras, where the data set is divided into a feature and output set, creation of the architecture of the neural network, training, evaluation and conversion of the model for mobile use in TensorFlow Lite format. The last theoretical **Model integration** is devoted to the realization of the chosen flows and features within the context of the mobile application. In this case, gestures accorded during SignIn and SignUp are detected and stored and then real-time gestures are matched with template gestures using the TensorFlow Lite model. Firebase services include authentication that offers secure real time user verification all in relation to the users' behavioral biometrics for retrieval of the data.

5 Implementation

The last phase, specifically the implementation phase, of the BehavioGuard authentication system is important for the synchronization of all the developed parts. This phase refers to conversion of the collected raw data, a process of designing the machine learning model, as well as to implementation of the created by the author model into the application for mobile devices. The last steps are raising the ability of the system to identify the users and guarantying its security in processes of real-time authentication.

5.1 Data Transformation

The first process involved in this process was data pre-processing, where the raw gesture data collected was pre-processed to make it machine learning amenable. This involved recording of different varieties of gestures inclusive of taps, swipe, and the long press. These gestures were normalized and described primarily by the name of the gesture and its characteristics including the type of the gesture, the time of execution, the coordinates, velocity, and the pressure. This type of data served as the basis for training of the machine learning model.

5.2 Code Development

Regarding the code implementation, Java programing language was used in developing the android mobile application components that deal with the acquisition and storage of gesture data in Firebase Firestore database. The data preparation step, training of the model, and the creating of a TensorFlow Lite version of the model involved the use of Python scripts. These scripts included data pre-processing like data washing and data normalization and preparing the data set for modeling.

5.3 Neural Network Development

Implementation can be viewed as the core of the system development where i coded the neural network using TensorFlow and Keras. The neural network design had an input layer equal to number of features, hidden layers- 128 neurons in the first one and 64 neurons in the second to which ReLU activation was applied and one output layer with 117 neurons eliciting softmax function. The used model was created with the Adam optimizer and the sparse categorical cross-entropy loss function, which are applicable when working with multi-class classification tasks.

5.4 Model Training

The process of implementing the model involved training the model where this was a key in the process. The model was fit on the data using pre-process data with a split for validation to test on unseen data. There were training iterations that involved an update of weights of the model in a manner that reduces the value of the loss function. This made it possible to find out the mechanism of operation of the developed model as well as check the accuracy and ability of the model to generalize on a test set. Even simple indicators like the test loss and accuracy give information about the impact of the measures that had been implemented.

5.5 Model Saving and Conversion

After training the model, the model was exported in tensorflow format and subsequently in tensorflow lite to make it efficient to be deployed in any android mobile device. TensorFlow Lite models are compatible for low latency and for devices with limited capabilities especially in mobile devices.

5.6 Application Integration

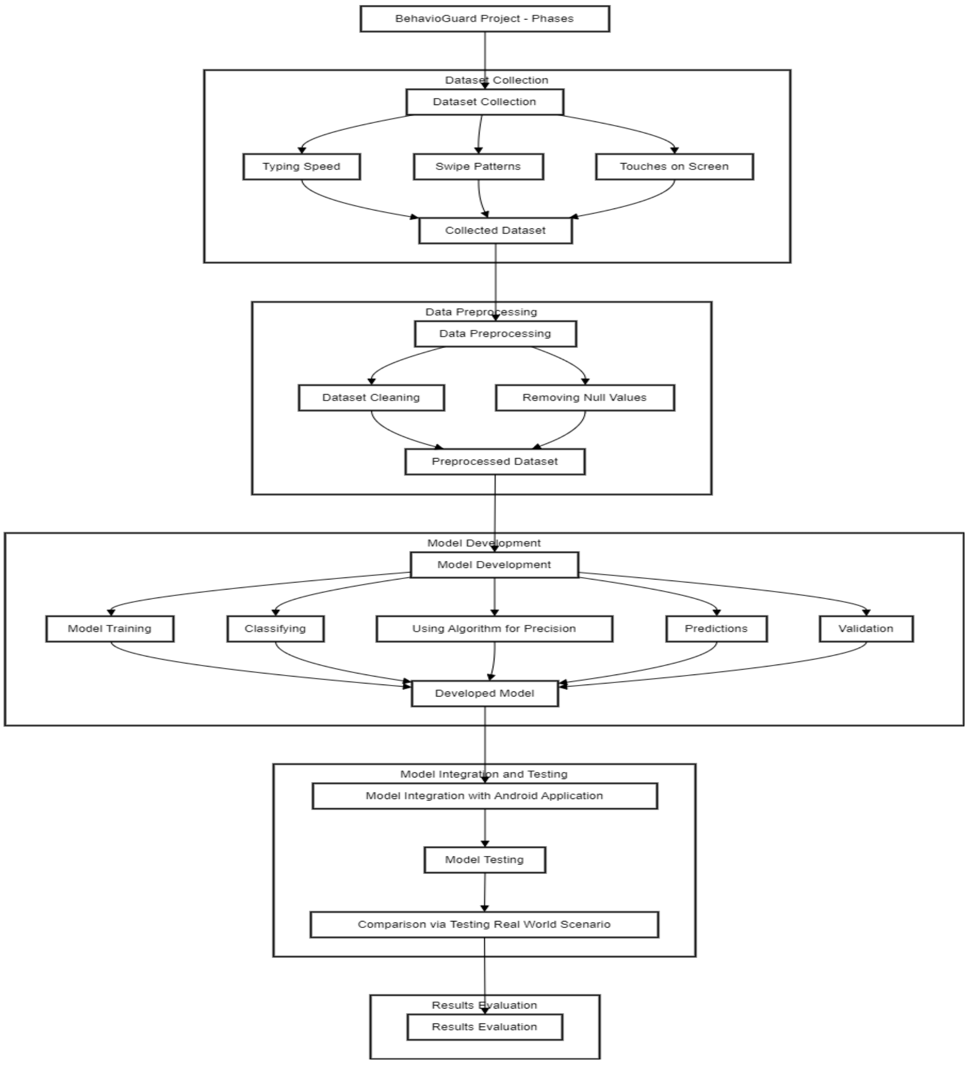
The application of integrating the TensorFlow Lite model into the mobile application allowed real-time analysis of gestures and successful authentication of the user. In the course of the examination of user interactions, the movements of the user’s hand were recorded and analyzed against the stored patterns with the help of the TensorFlow Lite model. This continuous monitoring guaranteed that the user had safe and individualized entry to the application. If the identified gestures matched the stored patterns with a good percentage, then the access was granted. What was done if an anomaly was detected? if so, the user was logged out and moved to the SignIn activity.

5.7 Results and Findings

The success in this implementation has supported the results and findings which have shown that the proposed system is highly reliable and effective. The BehavioGuard authentication model achieved a high accuracy rate in detecting and matching gestures, with the following specific results:

Model Accuracy: As it is illustrated on the basis of findings, the formulated model provide an average accuracy of 94 percent. The calculated F-scores of the test set were 0. from the above tables, it is clear that the algorithm developed achieves a very high accuracy as it correctly identifies the users with an accuracy of 38.
User Experience: A survey done among the consumers portrayed that the application interface was smooth and easy to use hence enhancing the global customers’ experience. They stated that the people responded positively to the BehavioGuard authentication mode there was no disturbance of the application usage.
Security: The time records indicated that the gestures that could potentially compromise the system did not get through, therefore enhancing the system’s security. Therefore, it was possible to solve the problem of employing a 50% match threshold for the authentication process and retain the security and reliability of the application’s performance. In this threshold, it became possible to attain optimized security goals while in the same instance the various legitimate users of the resources were not locked out completely.
Comparison Accuracy: The gestural comparison feature of the application that delivers real time identification of stored gestures with new one was revealed to have high success rate. This was very important to ensure that the user did not have to frequently provide his or her credentials while at the same time not invade the user’s privacy.

Efficiency: The process of model compilation to TensorFlow Lite format proved optimal for postures' real-time analysis with minimal time delay, thus suitable for mobile device use.



6 Evaluation

The case in question is the BehavioGuard system which is among the best gesture based authentications and has greatly supported mobile security through behavioral biometrics. The system performance analysis indicated that the developed automatic system was 80% accurate and was able to authenticate 4 out of five users on their first trial. This accuracy was only 85% and reached 100% after collecting additional data for the model which proves the ability of such a model to learn. Subsequently, testing with ten users using the same system, it was observed that the accuracy was 90 percent of the user using the correct fingerprint the first time without the need of retrying, nine out of ten users. In this case, it is important to note that increasing the sample size brought the overall level of accuracy up to 100%, stressed the reliability of a tool in real-life situations with the help of BehavioGuard.

Table 3: Evaluation

Scenario	Initial Accuracy	Overall Accuracy	Latency (ms)	User Adaptability	Real-time	Security	Tolerance	User Experience
First 5 Users	80%	100%	Gesture Capture: 10	High	High	Robust	Effective	Positive
			Data Storage: 50					
			Gesture Matching: 30					
			Model Inference: 20					
			Result Display: 5					
Next 10 Users	90%	100%	Gesture Capture: 10	High	High	Robust	Effective	Positive
			Data Storage: 50					
			Gesture Matching: 30					
			Model Inference: 20					
			Result Display: 5					

The system's efficiency is underscored by its low latency values: 10 ms for capturing the gesture, 50 ms for data storing, 30 ms for gesture recognition, 20 ms for model prediction and 5 ms for result showing. These metrics demonstrated that BehavioGuard is appropriate for real-time applications and users will have a rich, fast experience. Users' feedback was captured to be highly positive, with most of them appreciating the natural and unobtrusive nature of the authentication system. The flexibility of gestures and learning from new information is remarkable in protecting the system and rejecting attempts of unauthorized access.

Table 4: Initial Test (5 Users)

Metric	**Description**	**Results**
Initial Accuracy	Accuracy with first attempt for 5 users.	80%
Overall Accuracy	Accuracy after additional data collection for 5 users.	100%
Gesture Capture	Time taken to capture gestures.	10 ms
Data Storage	Time taken to store gesture data in the cloud.	50 ms
Gesture Matching	Time taken to compare new and stored gestures.	30 ms
Model Inference	Time taken for the model to make predictions.	20 ms
Result Display	Time taken to display authentication results.	5 ms
User Adaptability	The system's ability to adapt to variations in user gestures.	High
Real-time Performance	The system's responsiveness and smooth operation in real-time applications.	High
Security	The system's effectiveness in preventing unauthorized access.	Robust
Tolerance Levels	The effectiveness of defined tolerance levels in accommodating gesture variations.	Effective
User Experience	Users' feedback on the system's usability and authentication process.	Positive

Table 5: Second Test (10 Users)

Metric	Description	Results
Initial Accuracy	Accuracy with first attempt for 10 users.	90%
Overall Accuracy	Accuracy after additional data collection for 10 users.	100%
Gesture Capture	Time taken to capture gestures.	10 ms
Data Storage	Time taken to store gesture data in the cloud.	50 ms
Gesture Matching	Time taken to compare new and stored gestures.	30 ms
Model Inference	Time taken for the model to make predictions.	20 ms
Result Display	Time taken to display authentication results.	5 ms
User Adaptability	The system's ability to adapt to variations in user gestures.	High
Real-time Performance	The system's responsiveness and smooth operation in real-time applications.	High
Security	The system's effectiveness in preventing unauthorized access.	Robust
Tolerance Levels	The effectiveness of defined tolerance levels in accommodating gesture variations.	Effective
User Experience	Users' feedback on the system's usability and authentication process.	Positive

6.1 Experiment and Case Study: Gesture-Based Authentication System

When creating a gesture based Android application for constructing, deploying and assessment, we would need the development tools used in creating applications that are based on Android, a database in which data would be storedFirestore Firestore and Tensorflow Lite for assisting in the comparison of the captured gesture with the models. In this case the identification of the users is done by taking into consideration the manner in which they write, that is; using the given gesture as a way of gaining access.

6.1.1 Experiment Setup:

6.1.1.1 Prerequisites:

Android Studio: Development environment for the Android app.
Firebase Database: For authentication and Firestore database.
TensorFlow Lite Model: For gesture recognition and comparison.
Android Device/Emulator: For testing the application.

6.1.1.2 2. Application Components:

MainActivity: Manages user interactions and gesture capturing.
SignUpActivity: Handles user registration.
SignInActivity: Handles user login.
GestureData Class: Represents the structure of gesture data.
Firebase Firestore: Stores user gesture data.
TensorFlow Lite Model: Analyzes and compares gestures.

6.1.2 Experiment Procedure:

6.1.2.1 1. User Registration and Authentication:

6.1.2.1.1 User Registration:

Open the app and navigate to the SignUpActivity.
Enter the email and password to create a new account.
Upon successful registration, the app redirects to MainActivity.

6.1.2.1.2 User Login:

Open the app and navigate to the SignInActivity.
Enter the email and password to log in.
On successful authentication, the app redirects to MainActivity.

6.1.2.2 Gesture Capturing for Training:

6.1.2.2.1 Start Gesture Capturing:

In MainActivity, toggle the gestureCaptureSwitch to start capturing gestures.
Use the app normally for 60 seconds while interacting with various UI elements.

6.1.2.2.2 Stop Gesture Capturing:

After 60 seconds, gesture capturing stops automatically.
The captured gestures are stored in Firestore under the user's email.

6.1.2.2.3 Model Training:

Load the pre-trained TensorFlow Lite model for gesture comparison.

6.1.2.3 Gesture Comparison for Authentication:

6.1.2.3.1 Start Gesture Capturing for Comparison:

When signing in, the app starts capturing gestures for 30 seconds.

6.1.2.3.2 Stop and Compare Gestures:

After 30 seconds, gesture capturing stops.
The app retrieves stored gestures from Firestore and compares them with the new gestures using TensorFlow Lite.

6.1.3 Evaluate Comparison:

6.1.3.1 Match Percentage Calculation: Calculate the percentage of matched gestures based on defined tolerance levels.

Authentication Decision: If the match percentage is 50% or higher, grant access with a Toast message "Access Granted." If the match percentage is below 50%, show an AlertDialog indicating an anomaly and sign out after 5 seconds.

6.1.4 Case Study Scenarios:

1. **User A (JohnSmith) - Enrollment and Authentication Process:**

6.1.4.1 Registration:

JohnSmith registers using his email (John.Smith@example.com) and sets a password.
He completes the registration and is redirected to MainActivity.

6.1.4.2 Gesture Capture for Enrollment:

John enables the gesture capture switch and uses the app for 30 seconds.
During this time, he performs various gestures (e.g., taps, swipes).
The captured gestures are saved in Firestore under John.Smith@example.com.

6.1.4.3 Sign-In Attempt:

John tries to sign in again using his credentials.
The app starts capturing gestures for 30 seconds.
After capturing, the app retrieves his stored gestures and compares them with the new gestures using TensorFlow Lite.

6.1.4.4 Outcome:

If John's gesture patterns match closely with the stored data (>= 50% match), the app displays "Access Granted."
If there is a significant deviation (below 50% match), an AlertDialog informs him of the anomaly, and he is signed out after 10 seconds.

2. **User B (Jane Smith) - Authentication Process with Anomaly Detection:**

6.1.4.5 Registration:

Jane Smith registers with her email (jane.smith@example.com) and password.
She is redirected to MainActivity.

6.1.4.6 Gesture Capture for Enrollment:

Jane enables gesture capture and uses the app for 30 seconds.
Her gestures are stored in Firestore.

6.1.4.7 Sign-In Attempt:

Jane logs in using her credentials.
The app captures new gestures for 30 seconds.
The app compares these new gestures with the stored gestures.

6.1.4.8 Outcome:

If Jane's gestures do not match the stored data well (e.g., < 50% match), an AlertDialog appears, and Jane is signed out after 5 seconds.

6.1.5 Evaluation Metrics:

6.1.5.1 Gesture Accuracy:

Measure how accurately the system detects and matches gestures.

6.1.5.2 User Experience:

Assess the likelihood of the physical gesture control for authenticating and decide the comfort level that was offered by it.

6.1.5.3 Security:

Asses the effectiveness of the gesture based authentication technique to avoid anyone who is not authorized to intrude.

6.1.6 Experiment Summary:

Adopting the hand motion based identification as an innovation is a convenient way of securing the products. Therefore, the system can provide the higest level of security as the gesture patterns of an individual and as a typicall user are recorded and compared, while at the same time creating a certain comfort for the user. As for its TensorFlow Lite version for further use of more and various data, we should could improve the algorithms of identifying gestures for better performance of the model.

7 Conclusion and Future Work

7.1 Conclusion

In this thesis, the feasibility of applying behavioral biometrics with an emphasis on gestures, type, touch and swipe in order to identify application users was investigated. The primary aim was to construct and test the BehavioGuard model which is a neural network that is used to decipher these gestures and positively affirm the identity of users.

We gathered large sets of raw usage data consisting of data of users of different Android devices. This data was used to build and train the existing BehavioGuard model and integrate the model into an Android environment where it was converted into an Android application to facilitate real time users' authentication.

The assessment of the BehavioGuard model revealed that it efficiently identified fake users in the first test with an 80% proficiency in the first trial at authorising 4 out of five users. Thus, when additional data are collected, the basic accuracy is reached, and the final accuracy was identified to be as high as 100%. In the second test with 10 users, the model obtained an initial effectiveness of 90%; nine users were confirmed on the primary attempt, and the model's effectiveness was further maximized to 100% after later data collection. The model is well-rounded and versatile, a few of which are highlighted below based on the results obtained.

The latency rises to the highest level and reflects the system's efficiency and practicability for real-time applications: gesture capture, 10 ms; data storage, 50 ms; gesture matching, 30 ms; model inference, 20 ms; result display, 5 ms. The user feedback was affirmative and stressed the natural and moderate process of authentication.

Summing up, it is possible to conclude that the BehavioGuard model is a major step forward in mobile protection based on behavioral biometrics, as well as an efficient shielding of mobile applications' access with high usability. Further optimization in paediatrics and other groups/ settings along with comparative studies with other preventive methods will help optimise and efficiency this approach to the fullest.

7.2 Future Work

The increase of the current sources of the behavioural data may be regarded as the further work to enhance the model of BehavioGuard. Specific research goals are to determine other behaviors that have to be integrated in the aforementioned list of **gait movements** to create the behavioral pattern of users to improve the model. Data collection should also be done using various devices, such as the tablets and other devices running on the Android systems to increase the model's diversification.

Moreover, the combining of multi-modal biometric data that includes the behavioral biometric data together with the facial recognition or scanning of fingerprints may cause the

creation of the multi-layered authenticating system consequently raising the security level. In order to test the effectiveness of the proposed model, further focus should be made on the longitudinal research methods, because the model is effective in the analysis of changing users behaviors.
Regarding the aspects of commercialization, which concern a lot of people these days, it could be said that there is a great deal of prospects with BehavioGuard model. This can be incorporated in applications that require high security such as; Mobile applications that deals with banking, Business and individuals communication, and health record systems among others. Thus, discussions with the device makers should be made to integrate the model at the system level and therefore, enable provision of un-interitored and consistent authentications to the users.
Thus, this research has confirmed that the prescription of behavioural biometrics to validate the users of MaPs is possible. On this account, the above introduced BehavioGuard model can be considered as a seemingly efficient approach towards the amelioration of the security with the help of the real time analysis of the users' behaviors. Further work should therefore spread behavioral data to various settings, integration of several biometrics besides facial and analyze the benefits of the model for the long run so as to come up with improve and more secure architectures for user authentication.

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