Evaluating Deep Learning Models and Adversarial Attacks on Accelerometer-Based Gesture Authentication

Elliu Huang*  Fabio Di Troia*  Mark Stamp*†

October 28, 2021

Abstract

Gesture-based authentication has emerged as a non-intrusive, effective means of authenticating users on mobile devices. Typically, such authentication techniques have relied on classical machine learning techniques, but recently, deep learning techniques have been applied this problem. Although prior research has shown that deep learning models are vulnerable to adversarial attacks, relatively little research has been done in the adversarial domain for behavioral biometrics. In this research, we collect tri-axial accelerometer gesture data (TAGD) from 46 users and perform classification experiments with both classical machine learning and deep learning models. Specifically, we train and test support vector machines (SVM) and convolutional neural networks (CNN). We then consider a realistic adversarial attack, where we assume the attacker has access to real users’ TAGD data, but not the authentication model. We use a deep convolutional generative adversarial network (DC-GAN) to create adversarial samples, and we show that our deep learning model is surprisingly robust to such an attack scenario.

*Department of Computer Science, San Jose State University
†mark.stamp@sjsu.edu
1 Introduction

With the ubiquity of technology, authentication has become an essential part of everyday life. Passwords and PINs are the most common forms of authentication, but biometrics are also popular. Biometric authentication includes physiological (e.g., facial recognition and fingerprint) and behavioral (e.g., gait and keystroke dynamics) approaches [5].

While physiological biometric authentication has proven to be highly effective, sensors and equipment required for such approaches are usually costly. Additionally, attackers can sometimes bypass such a system if they have access to a copy of the required features [31]. On the other hand, behavioral biometrics not only have the potential to be cost effective, they may also be more secure, at least in cases where attackers have difficulty imitating the relevant features. Furthermore, the non-intrusive nature of behavioral biometrics may be considered desirable, in comparison to physiological biometric authentication.

Gesture-based authentication is a relatively recent behavioral biometric that has achieved promising results. There are various techniques for analyzing gestures, including acceleration, angular motion, 3D motion, and a mix of the three. Several machine learning techniques, including those we discuss in Section 2, have been applied to the gesture-based authentication problem.

In this research, we explore the effectiveness of deep learning techniques on gesture-based authentication. Our research is based on a new dataset that we have collected. Given that our tri-axial accelerometer gesture data (TAGD) are time series, we consider two time series classification (TSC) techniques: support vector machines (SVM) and one-dimensional convolutional neural networks (1D-CNN). When combined with feature extraction techniques, our SVM model provides for rudimentary analysis of our TAGD data, as well as a basis for comparison to our 1D-CNN model. We also generate adversarial samples using generative adversarial networks (GAN) and use these samples to explore the robustness of our 1D-CNN model against a realistic adversarial attack.

The remainder of this paper is structured as follows. Section 2 discusses relevant work in the field of gesture-based authentication and adversarial attacks on biometric authentication. Section 3 provides an overview of the dataset, including specific steps of the data collection process and data preprocessing techniques. Machine learning
techniques, including generating adversarial samples, and adversarial strategies are introduced in Section 4. We present our experimental results for our classification models and an adversarial attack in Section 5. Our conclusion and a brief discussion of future research directions are provided in Section 6.

2 Related Work

Relative to the vast research literature on behavioral biometrics, there is comparatively little work on gesture-based authentication. In this section, we provide an overview of research on gesture-based authentication and adversarial attacks on such security systems.

Most gesture-based authentication techniques can be categorized into two main methods, namely, touchscreen and motion gestures [11]. There are, however, studies that combine both into a single authentication system [8].

Touchscreen-based gesture authentication methods typically analyze touch dynamics, including various inputs recorded from a touchscreen interface such as finger size and pressure. One approach consisted of collecting finger behavior and position data and authenticated users via SVMs [3]. Another study employed particle swarm optimization to find patterns in touchscreen dynamics [24].

Motion gestures generally rely on accelerometer and gyroscope data to analyze the acceleration and angular motion of the mobile device. Prior research in this domain has applied dynamic time warping (DTW) [22], SVMs [23], and hidden Markov models (HMM) [15] to authenticate users. One gesture-based approach employed a more sophisticated method that involved the “leap motion” controller that collects 3D motion data and applied similarity thresholds to authenticate users [19]. Another approach analyzed full-body and hand-gestures in 3D space using two-stream CNNs [32].

Adversarial attacks on gesture-based authentication is not a well-researched area, but there are a handful of relevant studies in the general field of behavioral biometrics. One study analyzed behavioral mouse dynamics and found that deep learning authentication models were susceptible to adversarial attacks [28]. Adversarial samples have been generated using a fast gradient sign method (FGSM) to create perturbations in the data, with a gated recurrent unit (GRU)
then used to generate adversarial samples. Another study [1] analyzed the resilience of continuous touch-based authentication systems (TCAS) to adversarial attacks. These researchers found that their TCAS trained with the help of generative adversarial networks (GAN) had a lower false acceptance rate than that of vanilla TCAS. The paper [2] reports on experiments with randomization attacks on gesture-based security systems that use SVMs, and finds that their models are highly vulnerable to adversarial attacks.

Similarly, adversarial learning on time series classification has not seen much research. Most adversarial attacks involve small perturbations of the original data using state-of-the-art FGSM or basic iterative method (BIM) in order to “trick” a classification or regression model. A study of adversarial attacks on multivariate time series regression found that three of the most popular deep learning models—CNNs, GRUs, and long short-term memory (LSTM)—were highly susceptible to such attacks [25]. Another study also used FGSM and BIM to create small perturbations in time series data, which significantly lowered the classification accuracy of deep learning models for vehicle sensors and electricity consumption data [13].

3 Dataset

In this section, we give an overview of the data collected and specify the steps in the data collection process. We also include a discussion of data preprocessing and the feature engineering techniques that we have employed.

3.1 Data Collection

In this research, we collect users’ tri-axial accelerometer gesture data (TAGD) while the user holds a smartphone and writes their “signature” in the air, similar to the process in [18]. The accelerometer sensor of the Physics Toolbox Sensor Suite [10] was used to collect data. A screenshot of the application is shown in Figure 1. The tri-axial acceleration is represented as separate curves—the red curve represents acceleration along the x-axis, the green curve represents acceleration along the y-axis, the blue curve represents acceleration along the z-axis, and the white curve represents the total magnitude of acceleration. Data is collected at a frequency of 100 Hz, i.e., 100
data points per second. We performed data collection solely on the Apple iOS platforms in order to reduce the possibility of smartphone type being a confounding variable. We note that iPhone models varied from iPhone 8 to iPhone X.

![Figure 1: Screenshots of Physics Toolbox Sensor Suite app](image)

(a) Accelerometer sensor  
(b) App settings

Figure 1: Screenshots of Physics Toolbox Sensor Suite app

After installing the app, the user performs the following steps to collect signature data.

1. Tap the red button to start recording accelerometer data
2. Move the smartphone in the air to draw a signature
3. Tap the red button again to stop recording data
4. Upload data in the form of a CSV file into Google Drive

These steps were repeated 50 times to collect 50 signatures for each user.
In total, we collected 50 signatures from each of 46 different users. Users typically chose their initials as their signature, but they were free to create their own unique signature. Generally, the time to write each signature varied between 3 and 7 seconds, and the entire data collection process for one individual required about 20 minutes. Our dataset is freely available for use by other researchers at [17]. A sample of our TAGD data is shown in Figure 2.

![Sample tri-axial acceleration time sequence](image)

Figure 2: Sample tri-axial acceleration time sequence

### 3.2 Data Preprocessing

The raw tri-axial data is of variable length. As discussed below, we resize all signatures to the same size, as most traditional classification techniques require input data of a fixed size. We have applied several feature engineering techniques to the resulting time series.

#### 3.2.1 Feature Engineering

As noted above, each signature is a temporal sequence of tri-axial accelerometer data. First, we extract statistical features based on the acceleration for each axis, ignoring the sequential nature of the data. The resulting distributions vary—we compute the following statistical measures of shape, center, and spread for each of the three axes.
Length \((L)\) — The number of data points in the signature.

Mean \((\mu)\) — The center of the distribution is the mean

\[
\mu = \frac{1}{n} \sum_{i=1}^{n} x_i = \frac{1}{n} (x_1 + x_2 + \cdots + x_i)
\]

Median \((m)\) — The median is another measure of the center of the distribution.

Standard deviation \((\sigma)\) — The standard deviation

\[
\sigma = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (x_i - \mu)^2}
\]

measures the variability in the signature data.

Kurtosis \((k)\) — The kurtosis is computed as

\[
k = \frac{\sum_{i=1}^{n} (x_i - \mu)^4}{n \sigma^4}
\]

and it measures the weight of the tails relative to the center of the distribution and provides additional information related to the signature motion.

Skewness \((s)\) — The symmetry of the distribution, which is computed as

\[
s = \frac{\sum_{i=1}^{n} (x_i - \mu)^3}{n \sigma^3}
\]

can help us understand the “smoothness” of motion in a signature.

All of these features provide some information about underlying patterns in users’ signatures.

For each signature, we calculate a feature vector of the form

\[
(L, \mu_x, \mu_y, \mu_z, m_x, m_y, m_z, \sigma_x, \sigma_y, \sigma_z, k_x, k_y, k_z, s_x, s_y, s_z)
\]

consisting of the measures of shape, center, and spread of the distribution, as discussed above. This feature vector of 16 elements is utilized only in our SVM experiments, below.
3.2.2 Time Series Resampling

Since 1D-CNNs and GANs require feature vectors of fixed length, we use tslearn [30], we resize all the TAGDs to length 400. The resizing function in tslearn interpolates for arrays less than the target size. We chose to resample all the time series to length 400 since the median length of the sequences is 380, while the mean length is 400.

4 Implementation

In this section, we discuss the machine learning techniques that form the basis of our experiments. These techniques, namely, support vector machines, convolutional neural networks, and generative adversarial networks, will serve as the basis for our classification experiments in Section 5. We also introduce our strategies for adversarial attacks.

4.1 Support Vector Machines

Support vector machines (SVMs) are one of the most popular supervised learning techniques for classification and regression. SVMs attempt to find the optimal separating hyperplane between two labeled sets of training data [27]. However, a dataset need not be linearly separable, in which case we can employ the “kernel trick.” As depicted in Figure 3, the kernel trick maps the input data into a higher-dimensional space where it is more likely to be linearly separable. The kernel trick, together with “soft margin” calculations that allow for classification errors, makes an SVM an extremely powerful and flexible tool in the field of machine learning.

A classification problem with a small training sample size and high dimensionality is prone to overfitting [9]. Feature selection techniques can help to prevent this problem by discarding features, with minimal loss—or even improvements—in performance. In our SVM experiments, we used support vector machine recursive feature elimination (SVM-RFE) for feature selection. SVM-RFE consists of eliminating the least significant feature (based on linear SVM weights), then training a model on the reduced feature set. This process is repeated until the desired number of features is reached, or the performance degrades beyond acceptable limits.
4.2 1D Convolutional Neural Networks

Typically, convolutional neural networks (CNN) are associated with feature extraction and classification for images, which generally involves two-dimensional convolutional neural networks (2D-CNN). In such a model, 2D data (e.g., images) are fed into a CNN and classified via a final fully-connected layer.

In this paper, we do not consider images; instead, we have temporal sequences of fixed length. Such data is suitable for one-dimensional convolutional neural networks (1D-CNN). While not as common as 2D-CNNs, 1D-CNNs are used for signal processing and sequence classification, with numerous applications in biomedical and civil engineering [21].

The architecture of a 1D-CNN is analogous to that of a 2D-CNN, with the key differences being the dimensionality of the input data and the convolution operation. 2D-CNNs typically use a rectangular kernel that slides from left to right, top to bottom. In contrast, 1D-CNNs employ a kernel that spans some number of variables and slides along a vector.

4.3 Adversarial Strategy

We also consider how our deep learning models perform under adversarial attacks. While several studies analyze adversarial attacks involving small perturbations of the original data [20], we explore a
scenario where we assume the intruder has access to a real users’ gesture data. We test both poisoning and evasion attacks using learning models to generative adversarial samples; specifically, we use a type of generative adversarial network (GAN) to produce adversarial samples.

4.3.1 Deep Convolutional Generative Adversarial Networks

Two competing neural networks are trained in a GAN—a generative network and a discriminative network—with the generative network creating fake data that is designed to defeat the discriminative network. The two networks are trained simultaneously following a game-theoretic approach. In this way, both networks improve, with the ultimate objective being a model (discriminative, generative, or both) that is stronger than it would have been if it was trained only on the real training data; see [12] for additional details.

An overview of GAN structure is depicted in Figure 4. Among many other uses, GANs have been used to generate realistic adversarial samples.

![Figure 4: Overview of GAN structure](image)

We use deep convolutional GANs (DC-GAN) to replicate our time series data in a form that will serve as adversarial samples [4]. The generator and discriminator models are both based on 1D-CNN models. The generator essentially performs the functions of a convolutional layer in reverse—the input is an arbitrary sequence of values and it uses transposed convolution layers to shape the data into a desired form. The discriminator can be based on a traditional convolutional neural network. The fully-connected layer outputs a value between
−1 and +1, with a negative output indicating a fake sample and positive output indicating a real sample. The generator and discriminator are connected by a loss function, which provides feedback to both models. Over several epochs of training, the generator should become better at generating adversarial samples while the discriminator should become better at distinguishing between real and fake samples.

In our GAN model, the generator has an input consisting of a sequence of 100 values sampled from a normal distribution. After the data passes through three transposed convolution layers, the sequence of 100 values are transformed into a sequence of the same size as the TAGD, that is, 400 × 3. The discriminator model closely follows the architecture of the 1D-CNN classification model outlined above, with the major difference being the binary output of the fully-connected layer. The generator and discriminator are connected by a binary cross entropy loss function. In our experiments, we vary the number of training epochs to see how effective the adversarial samples are in breaking down our model.

In Figure 5, we have examples of TAGD generated using DC-GANs with different training epochs. The number of training epochs is directly related to how well the DC-GAN model can replicate data. As we can see in Figure 5 (a) and (b), the data is quite random doesn’t resemble the real TAGD in 2, whereas Figures 5 (c) and (d) appear closer to the real TAGD. As we train the DC-GAN more epochs, the adversarial samples resemble the real data more.

4.3.2 Adversarial Attack

Similar to [26], we “poison” our training dataset with adversarial samples generated from DC-GANs, meaning that we mix in adversarial samples with our real training dataset. Then, we train our 1D-CNN on the poisoned dataset and try to classify real data. The accuracy of classifying with the poisoned training dataset suggests how well our 1D-CNN can survive a poisoning attack while simultaneously indicating how well our DC-GAN can generate adversarial samples.

5 Experiments and Results

In this section, we present and analyze the results of the experiments outlined in the previous section. For our first experiment, we provide...
the results of a multiclass classification problem using SVMs, based on the statistical features discussed in Section 3.2.1. Then we apply a deep learning technique, 1D-CNNs, in the multiclass classification problem. Both of these techniques, SVMs and 1D-CNNs, produce strong results. Then we move on to adversarial learning where we use GANs to generate adversarial samples. With the GAN-generated adversarial samples, we show that our deep learning model is robust under a poisoning type of adversarial attack.

We use several metrics in our multiclass classification problem. The most basic metric we consider is the accuracy, which is calculated from a 46 by 46 confusion matrix. Of course, higher accuracy indicates a more successful model. We also measure the false acceptance rate (FAR), which is the rate at which a different user is classified as the actual user, and the false reject rate (FRR), which is the rate at which real users are mis-classified as other users. Since we are dealing with multiclass classification, we calculate FAR and FRR for each individual user and report the average for the 46 different users [14].
Intuitively, lower FAR and FRR indicates greater success in the classification model.

In our SVM experiments, we use SVM and RFE libraries from scikit-learn. In our 1D-CNN and GAN experiments, we implemented Keras libraries [6] to develop our models. For all the experiments, we use an 80-20 train-test split, i.e. 80% of the data is used to train the model, while the remaining 20% is used for testing.

5.1 SVM Results

We first considered rudimentary experiments with various kernels and values of parameters and found that a linear kernel with regularization parameter $C = 1000$ worked the best for multiclass classification. As a result, for all experiments in this section, we use an SVM with linear kernel and $C = 1000$.

Here, we train our SVM model on the feature vector described in Section 3.2.1 and use SVM-RFE to select the strongest features. We analyze the relationship between the number of features and the FAR, FPR, and accuracy.

Using all 16 features discussed in Section 3.2.1, the SVM achieved a 95% classification accuracy and 0.0014 and 0.057 FAR and FRR, respectively. These results (and more) are summarized in Figure 6.

As we eliminate features based on the rankings determined by SVM-RFE, the classification accuracy in Figure 6 (c) generally decreases, dropping to about 89% with 9 of the 16 features. This is still quite strong, considering the number of classes. As we can see from Figure 6, the accuracy generally decreases slightly as we eliminate more features, although the accuracy does not drop below 90% until we have eliminated 7 features. Similarly, the FAR is exceptionally low even as features are eliminated, staying below 1% for every combination of features. However, the FRR starts at around 5% and increases to more than 20% once we have eliminated 10 features.

5.2 1D-CNN Results

We also experiment with a 1D-CNN as our classification model, where the model follows the architecture in [7]. The 1D-CNN model is trained on temporal sequences of fixed length, as described in Section 4. The model performs one-dimensional convolutions along the time axis with RELU activation functions after each convolution layer. The
first convolution layer produces 128 filters, while the second convolution layer produces 256 filters. A dropout layer follows the convolution layers to prevent overfitting [16]. Then we have a 1D max-pooling layer to downsample the data and highlight the key features. The output of the max-pooling layer is passed through a flatten layer, which is then passed through two fully-connected layers. The last fully-connected layer produces the value that corresponds to the classification. This model is illustrated in Figure 7.

After fine-tuning hyper-parameters (dropout rate and number of filters), we moved on to experiment with kernel size and stride length. We found the accuracy hovered around 89% to 91%. According to [29], the performance of our 1D-CNN should be more receptive to changes in hyper-parameters involving the convolution layers.

We tested different combinations of kernels and stride lengths in the convolution layers. These results are summarized in Table 1. We
see that most of the results are fairly strong, ranging from a low accuracy of 90% to a high of 94%. Generally, as the kernel size increases, the accuracy increases. Similarly, as the stride length increases, the accuracy tends to increase. This is most likely due to the fact that larger kernels and stride lengths produce more refined features for the fully-connected layers.

| Table 1: Stride length versus kernel size |
|-------------------------------------------|
|                | 3   | 5   | 10  | 25  |
|----------------|-----|-----|-----|-----|
| stride=3       | 1   | 0.90457 | 0.89391 | 0.91276 | 0.90870 |
| stride=5       | 2   | 0.92696 | 0.93348 | 0.93630 | 0.93587 |
| stride=6       | 3   | 0.93087 | 0.94000 | 0.94109 | 0.94022 |

5.3 Adversarial Results

We trained a GAN to generate adversarial samples, and using these samples to determine whether our deep learning model is robust under adversarial attack. First, we determine how close our GAN-generated data is to real data through a simulated poisoning attack. Then we test how well the adversarial samples can evade an authenticator model.

As outlined in Section 4.3.2, we poison our training dataset with an increasing percentage of fake data. All real samples are always included, so any changes in classification accuracy should be caused by our adversarial (fake) samples. We trained our DC-GAN for different numbers of epochs and different numbers of adversarial samples. Generally, a higher number of epochs results in better imitations of
the original data. Increasing the number of adversarial samples in the training dataset gauges how well our 1D-CNN can resist large-scale poisoning.

The results of our poisoning attacks are given in Table 2. The accuracy remains relatively high at more than 90%, even for high training epochs and up to a 1:1 ratio of real to fake data. Classification accuracy does decrease slightly when there are more adversarial samples in the training dataset, but the loss in accuracy is not large. These results show that our 1D-CNN is highly resistant to poisoning attacks.

### Table 2: Adversarial attack results (1840 real samples)

| adversarial samples | epochs   |
|---------------------|----------|
|                     | 10       | 25       | 50       | 100      |
| 100                 | 0.93609  | 0.93130  | 0.94761  | 0.94565  |
| 250                 | 0.94587  | 0.94848  | 0.93783  | 0.94196  |
| 600                 | 0.94087  | 0.93978  | 0.94002  | 0.94152  |
| 1840                | 0.94000  | 0.94152  | 0.92239  | 0.93435  |

We conjecture that the reason for the limited success of our adversarial attack is that it is exceedingly difficult to generate realistic signatures of the type considered in this paper. While the real signatures in our dataset vary wildly, those that we generated using DC-GAN appear to exhibit more homogeneity. We plan to investigate this issue further in future work.

### 6 Conclusion and Future Work

Previous research has shown that SVMs are a viable techniques for accelerometer-based gesture authentication [18]. In this paper, we expanded on and improved upon previous work. First, we refined the feature selection process with SVM-RFE to select the best features, while maintaining a high classification accuracy. Then, we used deep learning models, specifically 1D-CNNs, for classification. We obtained strong results, with greater than 90% classification accuracy, slightly surpassing the accuracy of our SVM model. Lastly, we experimented with adversarial attacks on our 1D-CNN model, namely, poisoning and
evasion attacks. These simulate realistic attacks, assuming an intruder has access to the real data, but not the model itself. Our results indicate that our 1D-CNN is robust under such attacks, achieving greater than 90% accuracy for poisoning attacks and near perfect accuracy for evasion attacks.

For future work, additional machine learning techniques could be considered. For example, long-short term memory (LSTM) models could be used instead of 1D-CNNs, since LSTMs generally perform well on sequential data. Additionally, as mentioned in Section 5.3, we would like to explore alternative methods of generating adversarial samples to determine whether we can improve on the limited adversarial attack results obtained with DC-GANs.

References

[1] Mohit Agrawal, Pragyan Mehrotra, Rajesh Kumar, and Rajiv Ratn Shah. Defending touch-based continuous authentication systems from active adversaries using generative adversarial networks. arXiv preprint arXiv:2106.07867, 2021.

[2] Mohammad Al-Rubaie and J Morris Chang. Reconstruction attacks against mobile-based continuous authentication systems in the cloud. IEEE Transactions on Information Forensics and Security, 11(12):2648–2663, 2016.

[3] Ala Abdulhakim Alariki and Azizah Abdul Manaf. Touch gesture authentication framework for touch screen mobile devices. Journal of Theoretical & Applied Information Technology, 62(2), 2014.

[4] Sukarna Barua, Sarah Monazam Erfani, and James Bailey. Fc-cgan: A fully connected and convolutional net architecture for gans. arXiv preprint arXiv:1905.02417, 2019.

[5] Debnath Bhattacharyya, Rahul Ranjan, Farkhod Alisherov, Minkyu Choi, et al. Biometric authentication: A review. International Journal of u-and e-Service, Science and Technology, 2(3):13–28, 2009.

[6] Jason Brownlee. Deep learning with Python: develop deep learning models on Theano and TensorFlow using Keras. Machine Learning Mastery, 2016.
[7] Jason Brownlee. 1d convolutional neural network models for human activity recognition, Aug 2020.

[8] Attaullah Buriro, Bruno Crispo, Filippo Delfrari, and Konrad Wrona. Hold and sign: A novel behavioral biometrics for smartphone user authentication. In 2016 IEEE security and privacy workshops (SPW), pages 276–285. IEEE, 2016.

[9] Xue-wen Chen and Jong Cheol Jeong. Enhanced recursive feature elimination. In Sixth International Conference on Machine Learning and Applications (ICMLA 2007), pages 429–435. IEEE, 2007.

[10] Chrystian Vieyra. Physics toolbox sensor suite, 2016.

[11] Gradleigh D Clark and Janne Lindqvist. Engineering gesture-based authentication systems. IEEE Pervasive Computing, 14(1):18–25, 2015.

[12] Antonia Creswell, Tom White, Vincent Dumoulin, Kai Arulkumaran, Biswa Sengupta, and Anil A Bharath. Generative adversarial networks: An overview. IEEE Signal Processing Magazine, 35(1):53–65, 2018.

[13] Hassan Ismail Fawaz, Germain Forestier, Jonathan Weber, Lhasane Idoumghar, and Pierre-Alain Muller. Adversarial attacks on deep neural networks for time series classification. In 2019 International Joint Conference on Neural Networks (IJCNN), pages 1–8. IEEE, 2019.

[14] Margherita Grandini, Enrico Bagli, and Giorgio Visani. Metrics for multi-class classification: an overview. arXiv preprint arXiv:2008.05756, 2020.

[15] Dennis Guse. Gesture-based user authentication on mobile devices using accelerometer and gyroscope. Master’s thesis, Technische Universität Berlin, 2017.

[16] Geoffrey E Hinton, Nitish Srivastava, Alex Krizhevsky, Ilya Sutskever, and Ruslan R Salakhutdinov. Improving neural networks by preventing co-adaptation of feature detectors. arXiv preprint arXiv:1207.0580, 2012.

[17] Elliu Huang. Gesture dataset, 2021. Available from the authors upon request.

[18] Elliu Huang, Fabio Di Troia, Mark Stamp, and Preethi Sundaravaradhan. A new dataset for smartphone gesture-based authentication. In ICISSP, pages 771–780, 2021.
[19] Satoru Imura and Hiroshi Hosobe. A hand gesture-based method for biometric authentication. In *International Conference on Human-Computer Interaction*, pages 554–566. Springer, 2018.

[20] Hassan Ismail Fawaz, Germain Forestier, Jonathan Weber, Lhasane Idoumghar, and Pierre-Alain Muller. Adversarial attacks on deep neural networks for time series classification. *arXiv e-prints*, pages arXiv–1903, 2019.

[21] Serkan Kiranyaz, Onur Avcı, Osama Abdeljaber, Turker Ince, Moncef Gabbouj, and Daniel J Inman. 1d convolutional neural networks and applications: A survey. *Mechanical systems and signal processing*, 151:107398, 2021.

[22] Jiayang Liu, Lin Zhong, Jehan Wickramasuriya, and Venu Vasudevan. uwave: Accelerometer-based personalized gesture recognition and its applications. *Pervasive and Mobile Computing*, 5(6):657–675, 2009.

[23] Duo Lu, Kai Xu, and Dijiang Huang. A data driven in-air-handwriting biometric authentication system. In *2017 IEEE International Joint Conference on Biometrics (IJCB)*, pages 531–537. IEEE, 2017.

[24] Yuxin Meng, Duncan S Wong, Roman Schlegel, et al. Touch gestures based biometric authentication scheme for touchscreen mobile phones. In *International conference on information security and cryptology*, pages 331–350. Springer, 2012.

[25] Gautam Raj Mode and Khaza Anuarul Hoque. Adversarial examples in deep learning for multivariate time series regression. In *2020 IEEE Applied Imagery Pattern Recognition Workshop (AIPR)*, pages 1–10. IEEE, 2020.

[26] Luis Muñoz-González, Bjarne Pfitzner, Matteo Russo, Javier Carnerero-Cano, and Emil C Lupu. Poisoning attacks with generative adversarial nets. *arXiv preprint arXiv:1906.07773*, 2019.

[27] Mark Stamp. *Introduction to machine learning with applications in information security*. CRC Press, Taylor & Francis Group, Boca Raton, FL, 2018.

[28] Yi Xiang Marcus Tan, Alfonso Iacovazzi, Ivan Homoliak, Yuval Elovici, and Alexander Binder. Adversarial attacks on remote user authentication using behavioural mouse dynamics. In *2019 International Joint Conference on Neural Networks (IJCNN)*, pages 1–10. IEEE, 2019.
[29] Wensi Tang, Guodong Long, Lu Liu, Tianyi Zhou, Jing Jiang, and Michael Blumenstein. Rethinking 1d-cnn for time series classification: A stronger baseline. *arXiv preprint arXiv:2002.10061*, 2020.

[30] Romain Tavenard. tslearn documentation, 2021.

[31] Cong Wu, Kun He, Jing Chen, Ziming Zhao, and Ruiying Du. Liveness is not enough: Enhancing fingerprint authentication with behavioral biometrics to defeat puppet attacks. In *29th {USENIX} Security Symposium ({USENIX} Security 20)*, pages 2219–2236, 2020.

[32] Jonathan Wu, Prakash Ishwar, and Janusz Konrad. Two-stream cnns for gesture-based verification and identification: Learning user style. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops*, pages 42–50, 2016.