Audio is one of the most used way of human communication, but at the same time it can be easily misused by to trick people. With the revolution of AI, the related technologies are now accessible to almost everyone thus making it simple for the criminals to commit crimes and forgeries. In this work, we introduce a deep learning method to develop a classifier that will blindly classify an input audio as real or mimicked. The proposed model was trained on a set of important features extracted from a large dataset of audios to get a classifier that was tested on the same set of features from different audios. Two datasets were created for this work; an all English data set and a mixed data set (Arabic and English). These datasets have been made available through GitHub for the use of the research community at [https://github.com/SaSs7/Dataset](https://github.com/SaSs7/Dataset). For the purpose of comparison, the audios were also classified through human inspection with the subjects being the native speakers. The ensued results were interesting and exhibited formidable accuracy.

Keywords Speech impersonation, Speech mimicry, Audio forensics, Neural Network, Deep Learning, Human mimicry detection

1 Introduction

*By the time the truth arrives, lies have already destroyed the countryside.*

– A Pushto proverb

*The world today is such that whatever people don’t know about you, they create. They piece together what they hear from rumours, social media as well as assumptions & lies. It spreads really fast by the touch of a button...*

– Mufti Menk

This is an age of mendacity, backed up by digital art; lies are spreading lot faster than truth, especially through social media platforms. We already had fake multimedia content in the form of texts, audios, images and videos but now we have what is referred to as ‘deep fakes’, thanks largely to the mushroom growth of deep learning algorithms. High quality fake audios/videos are commonplace and, sometimes, threatening to ruin lives. Add to it statistics and you...
would find keen recipients everywhere in the world, in this post-truth era, from almost every age group and with every educational background. In the words of Mark Twain, "There are three kinds of lies: lies, damned lies, and statistics." At the same time, we cannot undermine the importance of circumstantially correct and available media, nor can we decrease the importance of Statistics.

Audiovisual media is one of the most important instruments to highlight not only atrocities/genocides across the globe but also fixing the responsibility of a given crime on the guilty. Its importance in a court of law, as well as the court of the people, cannot be underestimated. Hence we cannot trash altogether important means of evidence merely on the suspicion that these may be fakes. There has to be criteria to evaluate a given audio/image/video or other multimedia content.

Digital Multimedia forensics has obtained a lot of attention during the past decade. Most of the work has been generally focused on Image forgery detection [43] with copy/move forgery detection taking a lion share [28]. In comparison, digital audio forgery detection has not got that much attention. It is important in multimedia forensics to ensure the authenticity and integrity of the data in hand before handling it as an evidence. The primary focus of audio forensics is to establish the integrity of the audio, whether it is real or fake, and identify the real person(s) talking. The goals may be diverse, ranging from using it as evidence in a court of law to preempting social media or paparazzi rumors. Digital impersonation encompasses ways to produce a speech that may deceive people/machines into identifying it with a legitimate and authentic source, resulting in a social or economic loss. One important aspect of audio impersonation deals with mimicking someone’s voice to attribute to him/her something which was never said in one go.

Due to the availability of skilled voice actors detection of non-machine human audio mimicry is still a challenge, especially if it is blind, i.e. the partial or complete absence of the original. This difficulty, to blindly distinguish between real audios from mimicked audios, forms the basis of the research problem being addressed in this work. To be specific, our research problem is characterized by the following question:

*Can we come up with a method to blindly classify a given audio as human mimicked (faked) or otherwise (real)?*

The recent advances in Machine Learning (ML) - especially neural networks and deep learning - can be exploited in forgery detection in audiovisual data. With the potential amount of available data being huge, deep learning can be the best way to classify. The idea is to extract important features from the a lot of audios and feed it to a neural/deep network that will help the model learn how to identify the real audios from faked audios.

The rest of the paper is arranged as follows. Section 2 briefly describes the background speech processing concepts needed for the comprehension of this article. The related work from literature is outlined in Section 3 which is followed by Section 4 to introduce our dataset for this work. Section 5 explains our methodology which is then trained and tested on the dataset in Section 6 that analyses all the ensued results. Section 7 concludes the paper.

## 2 Speech Processing

It is important to know the difference between audio and speech. While an audio is a waveform data in which the amplitude changes with respect to time, speech is the oral communication [1] and pertains to the act of speaking and expressing thoughts and emotions by sounds and gestures. The human brain processes and analyses everything around to help the body with the right response or reaction and it does the same for the voices [2]. To be able to hear and process a voice, the inside of a humans ear is equipped with small hair of various sizes; some are short and respond to resonate with low frequency voices while others are long that resonate with the high frequency voices. Each of these hair is connected to a nerve that carries a signal to the brain for processing [47].

An audio signal is a representation of sound in function to the vibration of sound that is audible to human ear [3]. Audio frequency [4] is the periodic variation of sound, with the human audible frequency being 20 Hz to 20 kHz [5]. For a machine, the processing of an audio is different from humans. In order for the machine to get sound it should have a the needed devices that are able to record and save the audio in machine processable formats like mp3, WMA, Wav etc.

Features from speech signals can be broadly classified as Temporal and Spectral features. The temporal features are time domain features having simple physical interpretation and easy to compute. Examples are signal’s energy, maximum amplitude, zero crossing rate, minimum energy etc [29]. Spectral features, on the other hand, are frequency based features that are extracted after passing the time domain signal to the frequency domain using Fourier or other similar transforms. Examples are frequency components, fundamental frequency, centroid, spectral flux, spectral density, roll-off etc [29]. In the context of audio signals such features may be helpful in the identification of pitch, notes, rhythm and melody etc.
Spectrum and cepstrum are two important frequency based concepts in audio processing. A spectrum is mathematically a Fourier transform of a signal which converts a time-domain signal into frequency domain \[49\], i.e. spectrum is the audio signal in frequency domain. A cepstrum is the log of the magnitude of the spectrum followed by an inverse Fourier transform. That’s why its domain is neither frequency nor the time; its domain is called quefrency \[49\]. Cepstrum can be said of as a sequence of numbers that characterize a frame of speech \[8\]. Since the Fourier transform is a linear operation, so is consequently the cepstrum; the spectrums of the wavelet and reflectivity series are additively combined.

Following are some important features exploited in speech processing:

- **Zero crossing rate**: It indicates the number of times the value of the signal changes between positive and negative and vise versa. It is also used to measure the noise in a signal, and it usually gives high value in case of a noisy signal \[35\].
- **Spectral centroid**: It is a feature based on frequency which indicates the location of the center of mass of the spectrum. In audios it is known as a good predictor of “brightness” of a sound \[12\].
- **Spectral roll off**: This feature is used to differentiate between the harmonic sound (below roll off) and the noise sound (above roll off). It is known as the energy spectrum under a specific percentage that is defined by the used (85% by default) \[11\].
- **Spectral bandwidth**: The difference between the higher and lower frequencies in a group of continuous frequencies.
- **Chroma**: representation for audio where the spectrum is divided onto 12 bins representing the 12 distinct semitones (or chroma) of the musical octave.
- **Root Mean Square Energy (RMSE)**: Represents the energy of the signal, and shows how loud the signal is \[10\].
- **Spectral flux**: measures how quick the the power spectrum of a signal is changing, and it is calculated by comparing the changes of the power spectrum between one frame and the frame before it \[6\].
- **Spectral density**: It is the measure of signal’s power content against frequency \[14\].

**Cepstral Features**: These are, as stated above, quefrency domain features with the following being considered important:

- **Mel Frequency Cepstral Coefficients (MFCC) \[19, 39\]**: MFCCs are widely used features for speech recognition. The Mel-frequency scale represents subjective or perceived pitch as its construction is based on pairwise comparisons of sinusoidal tones. The conversion between Hertz \(f\) and Mel \(m\) frequencies can be generalized as:

\[
m = 2595 \log \left( 1 + \frac{f}{700} \right) \tag{1}
\]

\[
f = 700(10^{m/2595} - 1) \tag{2}
\]

MFCCs are obtained by applying a short time Fourier transform to window based slices from the audio signal, followed by calculating the power spectrum and consequently filter banks (triangular in shape). The filter bank coefficients are highly correlated and one way to de-correlate them is by applying a Discrete Cosine Transform DCT to get a compressed representation in the form of MFCC. Typically, MFCC 2-13 (i.e. 12 coefficients) are kept and the rest are discarded \[9\].

- **Gammatone Frequency Cepstral Coefficients (GFCCs) \[55\]**: used in a number of speech processing applications, such as speaker identification. A Gammatone filter bank approximates the impulse response of the auditory nerve fiber thus emulating human hearing and its shape can be likened to a Gamma function \(e^{-2\pi (f_c) b t}\) modulating the tone \(\cos(2\pi f_c t + \phi)\) \[7\]:

\[
g(t) = a t^{n-1} e^{-2\pi (f_c) b t} \cos(2\pi f_c t + \phi) \tag{3}
\]

Where \(a\) is peak value, \(n\) the order of the filter, \(b\) the bandwidth, \(f_c\) the characteristic frequency and \(\phi\) is initial phase. \(f_c\) and \(b\) can be derived from ERB scale, using the following \[31\]:

\[
ERB(f_c) = 24.7 \left( 4.37 \frac{f_c}{1000} + 1 \right) \tag{4}
\]

\[
b = 1.019 \times ERB(f_c) \tag{5}
\]

For GFCC, FFT treated speech signal is multiplied by the Gammatone filter bank, reverted back by IFFT, noise is suppressed by decimating it to 100 Hz and rectified using a non-linear process. The rectification is carried out by applying a cubic root operation to the absolute valued input \[31\]. Approximately, first 22 features are called GFCC and these may be very useful in speaker identification. For a concise comparison on MFCC and GFCC, the reader can further consult \[55\].
3 Related work

The output of *voice impersonation* must be convincing both to humans and machines in being naturally uttered by the target speaker. This requires mimicking the signal qualities, like pitch, as well as the speaking style of the target [23]. In this age of deep fakes, seamless machine-based impersonation is a reality. The method in [23] relies on using a neural network-based framework that uses Griffin-Lim method [24] which can learn to mimic a person’s voice and style and then produce a voice that mimics the persons’ voice. *Voice cloning* technologies can learn the characteristics of the target speaker and utilize prepared models to mimic a person’s voice from only a few sound samples. The developments in cloned speech generation technologies can create a fake machine speech that is similar to the real voice of the target speaker [55]. There have been researches efforts focusing on how to detect this kind of audio and how to enable systems to recognize them.

*Voice disguise* refers to altering one’s voice deliberately to conceal one’s identity. Impersonation is concerned with a voice disguise aimed at sounding like another person who exists [20]. While impersonation may be easily detectable, it is a hard task to trace back a disguised voice, of presumably a person who never existed, to the original speaker. A study in [50] reaffirms the importance of phonetically trained specialists in subjective voice disguise identification after an untrained audience failed to identify known speakers in case of falsetto disguise. A study along similar lines [20], reports that naive listeners can better distinguish between an impersonator and a target rather than identifying voice disguise. Readers are recommended a review of similar studies [42]. The system proposed in [18] relies on the magnetic field produced by loudspeakers to detect machine-based voice impersonation attacks. The reported results in combination with a contemporary system against human impersonation attacks, are incredible, viz. 100% accuracy and 0% EER.

Even an extensive work, like [52], does little to touch the subject of impersonation, especially the human mimicry, i.e. mimicking someone’s voice to attribute to him/her something which was neither ever said nor uttered in one go. Here we are talking of an audio that has never been tampered; other than the usual pre-processing, filtering and compression etc. As of datasets, we do have audio forensic databases [34], but even these don’t touch the aspect of impersonation in the form of human mimicking.

Human attempted voice impersonation (or voice imitation) is mimicry of another speaker’s voice characteristics and speech behavior [27] without relying on computer related spoofing; a fact ruling out the quest for technical artefacts in the suspected audio. The focus is mainly on voice timbre and prosody of the target [26]. Being a “technically valid speech”, mimic attacks may not be detectable, especially in Automatic Speaker verification (ASV) environments. A professional impersonator is likely to target all lexical, prosodic [21] and idiosyncratic aspects of the subject speaker; exaggeration may be inevitable [27]. The study reported in [41] states that speech patterns, pitch contours, formant contours, and spectrograms etc. from speech signals of maternal twins are at least almost identical, if not exactly the same. Hence even a mere verification may be a difficult task in the case of identical twins. Therefore, more exploration of discriminating speech features is needed, as suggested about half a century ago [46]. Even a paternal twin may be hand, as in a recent incident related to phone banking [15, 48], a non-identical twin mimic the voice of his brother, a BBC reporter, to deceive the system [13]. The literature contains many such incident of fraud [30].

The problem of human mimicry may be the earliest one addressed in the literature and can be traced back to as far as 1970’s. For example, an old study [44], employed four professional experts to identify voice disguises from the spectrogram of two sentences uttered by a sample of 30 subjects (15 reference + 15 matching) in undisguised as well as five disguised modes. Even without any disguise, the experts could go as far as 56% accuracy in matching the speakers. To classify speakers, another early days’ simulation [51] uses such parameters as fundamental frequency, word duration, vowel/nasal consonant spectra, voice onset time and glottal source spectrum slope. The parameters were estimated at manually identified locations from speech events within utterances. A later years study by Zetterholm [53] on a professional impersonator and one of his voice impersonations showed that the impersonator not only focused on the voice of the target, but also matched the speech style and intonation pattern as well as the accent and pronunciation peculiar to the target.

A voice impersonator may be identified by finding the features an typical impersonator chooses to exploit and what he ignores in the targeted voice, as had been tried in [54] whereby two professional and one amateur impersonators were asked to mimic the same target in order to observe whether they have chosen the same features to change with the
same degree of success. The work described in [32] used professional impersonators\(^2\) to mimic a person’s voice to identify the acoustic characteristics that each impersonator attempts to change to match the target. A comparison of the impersonated voices and the actual voice of the impersonator affirmed the importance of the pitch frequencies and vocal/glottal acoustics of the target speaker and impersonator. A similar work [16], involving three voice impersonators with nine distinct voice identities, recorded synchronous speech and Electro Glotto Graphic (EGG) signals. An analysis based on the EGG and the vocal traces - including speech rate, vowel formant frequencies, and timing characteristics of the vocal folds - led to the conclusion that each impersonator modulated every parameter during imitation. In addition, vowel pronunciations were observed to have a high dependency on the vowel category.

More recently, the work in [37] uses a Support Vector Machine (SVM) to create speaker models based on the prosodic features (intonation, loudness, pitch dependent rhythm, intensity and mimic duration in addition to jitter, shimmer, energy change, and various duration measures) from the original speech of celebrities and professional mimicry artists; as well as the original speech of the latter. A related work [45] uses Bayesian interpretation in combination with SVM. A similar prosodic features-based work [22], analyzes the ability of impersonators to estimate the prosody of their target voices while using both intra-gender and cross-gender speeches.

4 The Dataset

It seems that a standard dedicated speech impersonation database may not be publicly available, e.g. the study reported in [17] used the YOHO database that was designed for ASV systems. The best one can get is to collect from online sources, like YouTube, audios of celebrities and their mimicked versions by various professionals. Alternatively, one may exploit the public datasets, like voxceleb [40] that contain the original voices of celebrities; one may still vie for human mimicked version voices of these celebrities on YouTube.

Our goal is to blindly identify whether a given voice is mimicked or otherwise. hence for our experiments, a set of independent real and faked audios was required to create the dataset; real and faked voices uttered independent of what is being said and who said it and independent of the language. It is not necessary that both the real and faked voices of a given speaker are part of the dataset; in fact they should be mutually exclusive. Neither are the spoken words required to be identical.

To collect these data, we went through a number of social media apps and sites and downloaded the audios which were then edited to conform to the proposed model by limiting it to a maximum duration of 20 seconds in WAV format. One part of the dataset consists of all English audios (both real and mimicked) containing 1860 audio samples. The second part of the dataset contains a mix of both English and Arabic audios, 2026 in total. The dataset is available for public on GitHub (https://github.com/SaSs7/Dataset). The audio files are named so that the first four characters are digits to represent the index and the fifth character is either ‘r’ or ‘f’ to label the voice as real or faked, respectively.

5 The Proposed Method

The method we used is inspired by the one described in [33] for recognizing the spoken digits (0–9) from the audio samples of six people.

The proposed model is outlined in Fig. 1 that follows the steps given below:

5.1 Input

The input is the WAV files from our dataset described above that are stored in a suitable data structure. The model works in labeling our data based on the last letter (‘f’ or ‘r’) in the name of the file before storing it in a separate array of labels. The array is mapped to a separate perspective array of features obtained after the subsequent two steps.

5.2 Feature extraction

The model works on extracting the needed features using the Python librosa [38] package. The main features we relied on were RMSE (E for energy), Zero crossing rate, Spectral centroid, Spectral roll off, Chroma, MFCCs (we took 20). These features are already defined elsewhere.

\(^2\)One interesting aspect of mimicry detection, in addition to employing professionals, could be to employ twins [46], at least of reference.
5.3 Transforming the dataset

Using `sklearn.model_selection`, the model, the feature set is first partitioned to training and testing sets. During the training phase, the training set is dynamically partitioned to training and validation parts. By employing the `sklearn.preprocessing.StandardScaler` class, the data is normalized in order to better structure it for visualization and analyses. The data is standardized, which means that the will have a mean of 0 and a standard deviation of 1.

5.4 The Neural network

The next step is the nine-layer deep neural network outlined in Fig. 1 that follows a sequential model. The reason to choose the sequential model is its simplicity and the ability to add up more layers easily.

The model has alternating dense and dropout layers with a single flatten layer in the middle. The Dense layer is a fully connected layer based on the back-propagation function. The dropout layer is used for toning down too many feature associations during training in order to avoid over-fitting. In general, ReLU is the activation function, except the last layer where softmax is the activation function. Fig. 2 gives a snapshot of the layers involved in an example execution.

After preparing the model we pass on the data for training the model via the usual `fit()` function. We use the adam optimizer for its efficiency, manageable memory requirements and its amenability for larger data/parameters. As we have only two possible labels (real or faked), for better accuracy, the loss function is based on the sparse categorical cross entropy. The number of epochs were set to 140 which is the number of times the model will train before it completes the training process. The batch-size was set to 128 which the number of sample processed before the model is updated. The testing phase involved the usual prediction function (`predict()`) with subsequent comparison of the predicted labels with the actual labels from the dataset.

5.5 Reference Data

Even after a thorough search we were not able to find a reference method that could benchmark the research problem we are after. Hence it was decided to come up with reference data by inspection through human subjects/volunteers. We gathered a group of 10 native Arabic speakers and 20 native English speakers. Each volunteer would to listen to the audios from our dataset and tabulate it as real or faked as per his/her observation. Due to the scarcity of native English speakers, we had to contact the volunteers through social media and carry out the process live online.

6 Results

The model was trained and tested with audios from our two datasets already described in the previous section. The first set of chosen audios (recordings in English only) consisted of 1517 sample which were partitioned into 1383
training and 134 test samples. The second set (Mixed) had 1900 audios, recorded both in English and Arabic, which was partitioned into 1556 training and 344 test samples. The validation split was done dynamically during the training phase in both cases.

We can see from this figure that our model has a good learning curve and although we fixed the number of epochs to 140, most of the convergence is realized well before 40 epochs; only some refining need further epochs. The curves of loss decreases to a point of stability, although on can observe a small gap of test loss with the training loss.

The confusion matrix corresponding to the training of the model on 1383 samples of the English dataset was:

\[
\text{Train (all English)} \begin{pmatrix}
TP & FP \\
FN & TN
\end{pmatrix} = \begin{pmatrix}
691 & 2 \\
1 & 689
\end{pmatrix},
\]

where,

TP = True positives,
TN = True Negatives
FP = False Positives
FN = False Negatives.
Over the same dataset, the resultant confusion matrix par rapport the testing, based on 134 samples, was observed to be:

\[
\text{Test (all English)} = \begin{pmatrix}
68 & 6 \\
0 & 60
\end{pmatrix}
\]  

(7)

Based on the above confusion matrices, for all English dataset, the resultant training accuracy was found to be 0.9986 (99.86%) as against the testing accuracy of 95.5%. These results are interesting in the face of the fact that the method is blind and no additional information is made available to our method. Aside for accuracy, numerous relevant metrics were computed, as listed in Table 1. It can be seen that all the metrics exhibit enviable values.

| Metric                              | Formula                                      | All English Dataset (1517) | The Mixed Dataset (1900) |
|-------------------------------------|----------------------------------------------|---------------------------|--------------------------|
| Sensitivity/Recall/True positive rate (TPR) | \( \frac{TP}{TP + FN} \)                  | Training (1383) | 0.997 | Test (134) | 0.919 | Training (1556) | 0.995 | Test (344) | 0.872 |
| Specificity/True negative rate (TNR)     | \( \frac{TN}{TN + FP} \)                  |                           | 0.998 | 1.0 | 0.994 | 0.812 |
| Fall out/False positive rate (FPR)       | \( \frac{FP}{FP + TN} \)                  |                           | 0.0014 | 0.0 | 0.006 | 0.188 |
| Miss rate/False negative rate (FNR)       | \( \frac{FN}{FN + TP} \)                  |                           | 0.0029 | 0.081 | 0.005 | 0.128 |
| Precision/Positive predictive value (PPV) | \( \frac{TP}{TP + FP} \)                  |                           | 0.998 | 1.0 | 0.994 | 0.859 |
| Accuracy                               | \( \frac{TP + TN}{TP + TN + FP + FN} \)   |                           | 0.9986 | 0.955 | 0.994 | 0.846 |
| balanced accuracy (BA)                | \( \frac{Sensitivity + Specificity}{2} \) |                           | 0.9979 | 0.959 | 0.994 | 0.842 |
| \( F_1 \) Score                        | \( 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \) |                           | 0.997 | 0.958 | 0.994 | 0.865 |

Table 1: Metrics calculations for both the English and Mixed parts of the dataset.

With the mixed part of the dataset, the sample include 1900 English and Arabic audios. There were 1556 samples allocated to the training part and the resultant confusion matrix was:

\[
\text{Train (Mixed)} = \begin{pmatrix}
780 & 4 \\
5 & 767
\end{pmatrix}
\]  

(8)

The computed training accuracy was thus found to be 99.4% in classifying the real and faked audios. The test accuracy for the mixed part was however 84.2% as can be deduced from the following confusion matrix:

\[
\text{Test (Mixed)} = \begin{pmatrix}
170 & 25 \\
28 & 121
\end{pmatrix}
\]  

(9)

Table I sums up all the results par rapport both the all English and mixed parts of the dataset. For a better idea about the obtained results, the receiver operating characteristic (ROC) curves for both the parts are illustrated in Fig. 4.

(a) The English dataset

(b) The mixed dataset

Figure 4: Receiver operating characteristic (ROC) curves.

As already stated, due to the lack of a benchmark, we relied on human observers in order to highlight the achievement of our method. to this end, we got the data by adopting the strategy outlined in Section 5.5 above. By conducting the test
on two groups of people we got the the English native speakers were able to identify 85% of the English audios given as real or fake correctly. In contrast, the proposed model got 96% accuracy in classifying the real and faked audios using the all English dataset. With the native Arab speakers, 89% of the Arabic audios were identified correctly, however.

7 Conclusion

We were able to show how can neural network take audios and extract features and use them to classify the audios to faked and real. The model learnt the pattern and then it was able to differentiate real audios from faked audios. The performance of our model is proven by its accuracy which was 96% over the all-English data set and an accuracy of 84.5% with the mixed data set. A Comparison with results by inspection from human subjects proves that our model can identify real and faked audios with a better accuracy, as far as English language is concerned.

After conducting the human subject test and the results of the model test we found that there were some audios on which both tests agreed being faked audios, where in fact those audios were real, see Table 2. The probable cause, of the failure of the test participants in identifying those audios, may be the background noise that may have made them think that those audios were real.

| Language | Audio Id. | Human observers | Proposed Method | Ground Truth |
|----------|-----------|-----------------|-----------------|--------------|
| Arabic   | 0920f     | real            | real            | faked        |
|          | 0931f     | real            | real            | faked        |
|          | 0932f     | real            | real            | faked        |
| English  | 0001f     | real            | real            | faked        |
|          | 0003f     | real            | real            | faked        |
|          | 0005f     | real            | real            | faked        |
|          | 0006r     | faked           | faked           | real         |
|          | 0007f     | real            | real            | faked        |
|          | 0009f     | real            | real            | faked        |
|          | 0010f     | real            | real            | faked        |
|          | 0011f     | real            | real            | faked        |

Table 2: Matching wrong results by both the model and human observers.

As a future improvement, we first aim to collect more data to improve the Arabic dataset and make it available for researchers. Secondly, there is a need of diversity in the form of the inclusion of audios in other languages too. This may improve the classification capability of the model. Last but not least, deploying the model in mobile based software may help against impersonation offenses.

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