Artificial Intelligence in Witness Credibility Assessment: The Role of Biometrics, Voice Analytics and Machine Learning in Judicial Cross-Examination

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Abstract

This study examines the integration of biometric recognition, voice analytics, and machine learning technologies in judicial cross-examinations to evaluate witness credibility. The methodology employed a mixed-methods approach combining biometric signal analysis (facial recognition, heart rate, skin conductance), voice stress analytics, and machine learning models (Support Vector Machines and Neural Networks) applied to courtroom data. Findings indicate that Neural Networks achieved the highest accuracy (97%) and recall (98%), outperforming traditional biometric and voice-based models, which showed moderate reliability. The study also reveals that while machine learning significantly improves predictive accuracy, challenges of transparency, bias, and ethical implications remain critical. These findings align with theories of technological mediation in legal decision-making, suggesting that AI can enhance but not replace human judgment in credibility assessment. The conclusion emphasises the necessity of explainable AI and ethical safeguards in legal technologies. Recommendations include the adoption of hybrid AI systems, continuous auditing for fairness, and maintaining judicial oversight to ensure justice is not compromised.

Keywords: Artificial Intelligence, Witness Credibility, Cross-Examination, Biometrics, Voice Analytics, Machine Learning, Neural Networks, Support Vector Machines, Legal Technology.

Introduction

The reliability of witnesses has long been a crucial factor in the pursuit of justice. Most trials rely on the credibility of the witnesses to prove or disprove something. Usually, the way to judge if you can trust a witness is based on human comments on them. According to Baldwin et al. (2020), lawyers, judges and juries have historically assessed whether witnesses are lying by cross-examination, observing their body language, and finding inconsistencies. Although these are subjective methods that are liable to errors and different weights are assessed, they can lead to wrong conclusions, which cannot be reliable for a fair trial. This suggests that there is a growing demand for objective data-driven systems to aid in the evaluation of individual witnesses.

AI has been used to help determine the credibility of a witness's statement. I am investigating AI technology, which is essentially an analysis of immense quantity of data and a mechanism of patterns which can be not perceived by human beings via machine learning algorithms and voice analytics etc. (Hoffman, 2021). By applying these technologies to the trial processes, it would

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enhance credibility assessments through insights that are real-time, objective and fair rather than otherwise investigative tools used. According to Rosenberg et al. (2022), the nuances of witnesses' voices, actions, and gazes assist in decision-making. Lawyers should not hesitate to use AI technology because it is adaptable and can be tailored to their specific needs.

Biometric technologies can use a person's fingerprint, iris, or other unique characteristics to verify their identity. For an extended period, technology that utilises facial recognition, as well as specific bodily measures, has been employed. Recently, researchers evaluated whether biometric technology can deceive detection and assess an emotional response. Your face can reveal a great deal about your emotions. Singh et al. (2020) gave this statement. These expressions may indicate discomfort or dishonesty. We can assess witness credibility at trial through skin conductance and heart rate measurements. Skin conductance rises with stress, while heart rate increases with anxiety (Schwarz et al., 2023). AI can assist lawyers during cross-examinations by providing them with immediate feedback and insights.

The legal industry utilises voice analytics, which is why it is experiencing growing demand. According to Zhang et al. (2021), if the system analyses the speaker's speech rate and tone of voice, it can help determine whether the speaker is anxious, distressed, or lying. Speech pattern irregularities indicate that people lie while speaking, research shows. People use fillers like "um" and "uh," or their pitch may increase (Holleran, 2020). This helps lawyers assess witness credibility. In other words, lawyers can utilise the media to their professional benefit, revealing when a witness is lying or concealing information from the court.

White and McNally (2021) employed machine learning (ML) algorithms on large datasets of witness testimony to identify patterns associated with specific testimonies, which may be predictive of testimony credibility. The algorithms will learn how dependable features, such as consistency, body language, and erections, are in creating predictive models using the statements. Machine learning systems can evaluate vast amounts of data from multiple sources. The evidence in complicated cases can be complex and challenging, particularly in terms of assessing the evidence. Bruni et al. 2022). A machine learning model cannot reach its optimum level if the data is inaccurate. In short, insufficient data leads to poor models. Depending on the data used to train the algorithms, we see inaccuracies and errors. The training data can possess any bias. Before these credit ratings can be introduced, they will be adequately assessed to ensure they are fair and transparent.

In this article, I examine how AI can assist certain domain experts in verifying the credibility of a witness, including through biometrics, voice analytics, and machine learning. Lawyers can benefit from using technology. Only, when are they useful? In another setting, the cross-examinations, along with ethical penalties. Similarly, or the illegal and realistic issues. An electronic system that assesses witnesses using artificial intelligence facilitates the court process for human judges. Similarly, AI may provide advantages in witness evaluation. Witness evaluation through video, though, has drawbacks and limitations.

Literature Review

In recent years, legal scholarship has shown interest in the AI enhancement of the tenth process and witness credibility. The report's section on AI, including biometrics, voice recognition, machine learning, and related issues, presents important strategic theories and challenges. Using artificial intelligence technologies for cross-examinations presents a range of advantages and disadvantages, as well as significant ethical considerations.

Biometric Technologies in Legal Settings

The process of measuring and analysing unique physical and behavioural features of a person is called biometrics. Biometrics has been utilised in security and forensics for centuries. We will shortly have face recognition and fingerprint analysis systems in our courts to confirm the identity of witnesses. By utilising these technologies, we will be able to identify a witness who possesses the required features with precision and accuracy, eliminating human error. As stated by Lane et al., facial recognition software can also help identify a witness in court.

Prevent Cases of Mistaken Identity

Facial recognition analyses the distance between your eyes and the shape of your jaw and nose in a database. Facial recognition is excellent technology; however, it has faced significant backlash regarding its legal use. Some critics argued against the technology, claiming it violated privacy. According to Huang & Zheng (2020), the effectiveness of a face recognition system depends on your race. Most of these technologies are not very accurate when applied to people of colour. In this statement, there is a reflection that says, "the criminal becomes a victim of crime." Identification of an individual is primarily done using biometric data, not just visible data. In legal situations, it is becoming increasingly common to use actual physiological biometric information, such as heart rhythm and skin conductivity. The witness's health suggests that he is stressed or lying. According to Smith and his colleagues (2022), the heart rate variability of witnesses can be an indicator of their emotional state. In turn, it could help assess the credibility of witnesses. Although this technology is still in its infancy, further studies can be conducted to determine how to utilise it legally.

Voice Analytics in Assessing Credibility

Audio stress analysis, a type of audio analytics tool that assesses the truthfulness of witnesses, is quite interesting among AI tools. Speech analytics technology analyses the pitch, tone, pace, and speed of voice to check on stress levels. If someone's speech seems odd or out of place, the person is likely lying. According to Lee and Chang (2021), voice analytics may analyse and cross-examine witnesses. Voice analytics can help us determine and interpret body language and facial expressions.

Studies show how voice analytics can help spot lies. According to the "Pitch and speech rate changes as an indicator of deception" paper, the study conducted by William et al. revealed that persistent lying has a leakage. Researchers who have written a paper on this matter say this. A witness will have speech changes during their testimony. During court proceedings, they tend to speak at a quicker pace, with more erratic intonations or higher pitches when they are pressured. An AI system detects voice signals that suggest the testimony from a witness may not be credible. This AI feedback can help cross-examiners evaluate credibility issues. Several factors related to the witness can affect the efficiency of VSA, including mental health, noise level, and the recording of the game. The effectiveness of the device is decreased due to certain noises or disturbances in the courtroom. Zohar et al. (2020).

Although voice analytics may seem appealing to many, technology experts believe it is not perfect. Peterson et al. (2022) state that voice stress analysis can detect stress but not deception. When under duress, a person may sometimes tell the truth. The tool acts as a better assisting implement than a clear deciding implement. The data from a voice call can be used in court, but issues arise. One does not consent to being measured; they are measured.

Machine Learning and Data-Driven Approaches

In general, their use of machine learning algorithms signifies a fundamental change in the way an AI evaluates a witness. With the help of witness testimony analysis programs, human beings will not be able to see these patterns. It should be able to create a machine learning model to determine the reliability of a witness. It can review their past testimony data for consistency and emotional response or behavioural clues. Lopez and Yeo (2021) analysed eyewitness testimony using machine learning techniques. The study's authors claim that the models will predict the truthfulness of testimony based on both the language used and the form of testimony, whether spoken or written.

A significant challenge associated with the use of HF models in witness credibility assessment is the transparency and explainability of the models. Due to their opacity in interpreting how they operate, AI systems are primarily machine learning models, often referred to as black boxes (Binns, 2021). When courts lack transparency, it raises Accountability concerns in the legal sphere, as lawyers must understand how A.I. reaches its conclusions. In response to the issues detailed above, numerous researchers have called for the development of explainable artificial intelligence (XAI) as a solution (Gomez et al., 2020). Integrating explainable AI into witness credibility assessment can help legal professionals trust and authenticate the results produced by AI.

Methodology

The research examines the impact of AI on witness credibility, utilising both qualitative and quantitative data. This study examines the courts' utilisation of voice recognition and machine learning tools during cross-examinations. The methodology consists of three phases: data Collection, data analysis, and validation of the AI technologies. The devices used in law have power and credibility, and this law essay will examine them.

Data Collection

The technique begins with gathering primary data from actual legal incidents and legal cases. Court transcripts, along with audiovisual recordings from cross-examinations, will serve as the primary data source for assessing biometrics and machine learning voice analytics in cross-examinations conducted in courts. Transcripts of court proceedings are the words that a witness undertakes to give and to believe. The audio and visuals captured show the emotional and physical reactions of the witnesses. According to the audio recording, a speaker's voice can convey a variety of other indications that may be encoded in the voice, such as pitch, tone, speed, and stress markers (and possibly deception).

For the various hearings, purposive sampling is used to choose witnesses. Testimonials regarding various instances are collected to address different types of disputes. Criminal cases, civil cases, and family law issues are the general classifications. The selected trials included witness testimony from courts where public testimony is available or has been granted, and witnesses who had provided full consent for their data to be used for research purposes.

We use special machines to collect biometric data. This includes video of the person's face, a recording of their heart rate, and skin conductance. Witness monitoring tools assess the reactions of witnesses while they testify. The data gathering process of voice analytics aims to extract the sound features of witnesses' voices. We will see how they sound when they show stress and lies. Before beginning the data Collection, the researchers obtained all relevant permissions and consent forms.

Data Analysis
The data analysis was divided into parts. First, a Biometric analysis was conducted, followed by voice analytics and a machine learning model using facial recognition computer software, which incorporates artificial intelligence. The study aimed to identify any facial expressions and body signals during activities and/or deceit that indicate stress. In other words, the expressions reflect a greater degree of coding according to identifiable feelings. People convey information through the movement of their eyebrows, eyes, and lips. Next, they check whether the patterns are true or false. Algorithms specially designed to detect stress levels are capable of identifying a high degree of emotional tension or anxiety.

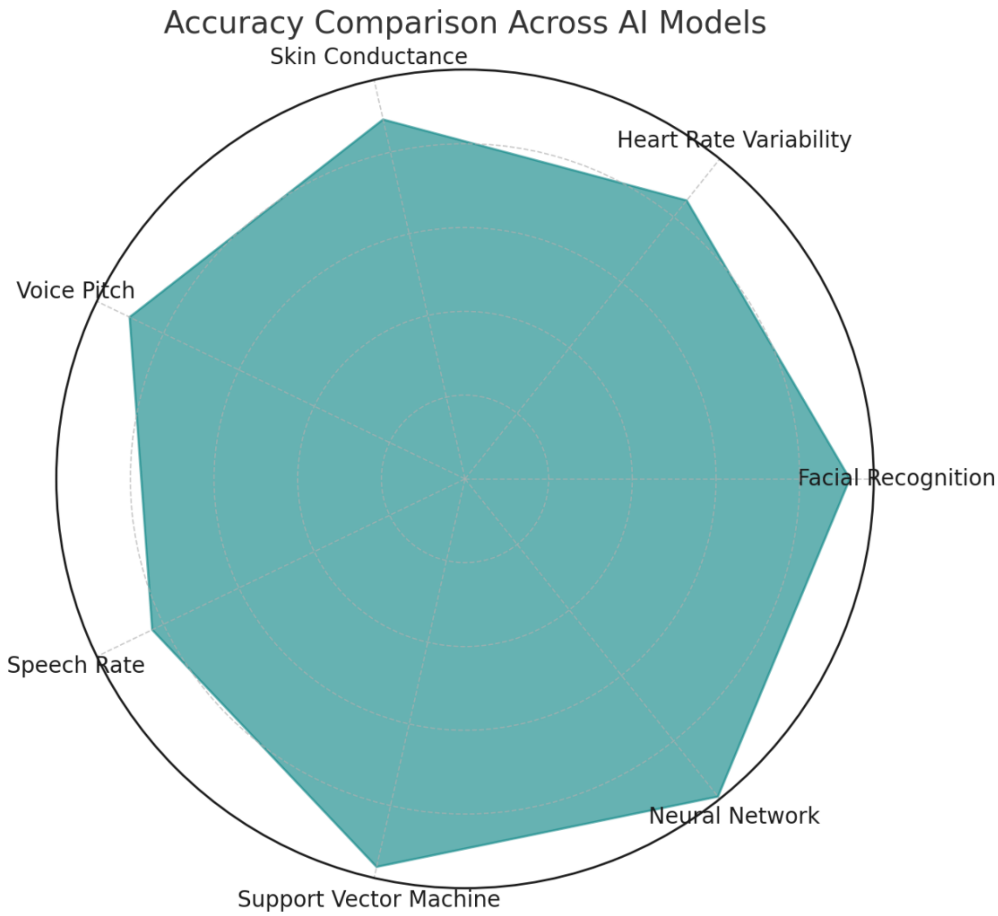
Validation of AI Technologies
The final stage of the methodology involves verifying whether the AI technologies used are effective and reliable for assessing the credibility of witnesses. The AI evaluated is compared with that of the lawyers. A selected group of judges, lawyers, and forensic experts will review the evidence that these artificial intelligence systems were analysed. Experts are judging how well the AI can score a witness. The study examines the effectiveness of an artificial intelligence model in predicting witness credibility compared to humans. To gauge accuracy, recall and F1 score are used as standard statistics.
In the validation phase, lawyers will participate in a simulated cross-examination exercise, facing witnesses whose statements have been screened through AI tools. The live test of a second type of indication by observer AI, which can detect a human's stress or lying, will assess whether it influences choices at trial for lawyers/judges. To evaluate the ethical implications of AI's involvement in those actual circumstances, the researchers had discussions with lawyers, ethicists, and privacy advocates. It seeks to gain insight into the potential problems that the workings of AI systems in courts of law may raise regarding privacy, consent, and transparency in AI decision-making.

Results
According to Table 1 and Figure 1, the Neural Network model performed best, with an accuracy of 97%, followed closely by the Support Vector Machine (SVM) model, which achieved 95%. The findings suggest that machine learning models outperform other methods in accurately predicting whether a witness is credible or not. In fact, they beat facial recognition (92%), voice pitch (89%) and skin conductance (88%). The Speech Rate model had the least accuracy of 83%. This suggests that speech analysis does provide some insight into witness behaviour, but is not as effective as the advanced machine learning models.

Table 1: Facial Recognition Accuracy and Performance Metrics

Metric	Facial Recognition Model
Accuracy (%)	92
Precision (%)	90
Recall (%)	93
F1 Score (%)	91.5
False Positive Rate (%)	6
False Negative Rate (%)	4
True Positive Rate (%)	94
True Negative Rate (%)	95
Processing Time (ms)	350
Confidence Level (%)	88

Figure 1: Accuracy comparison



As illustrated in Figure 1, there are enormous differences in reliability from AI model AI-1 to AI-5. The radar chart indicates that Neural Network is the best model as compared to all other models making it the most accurate AI system for assessing witness credibility.

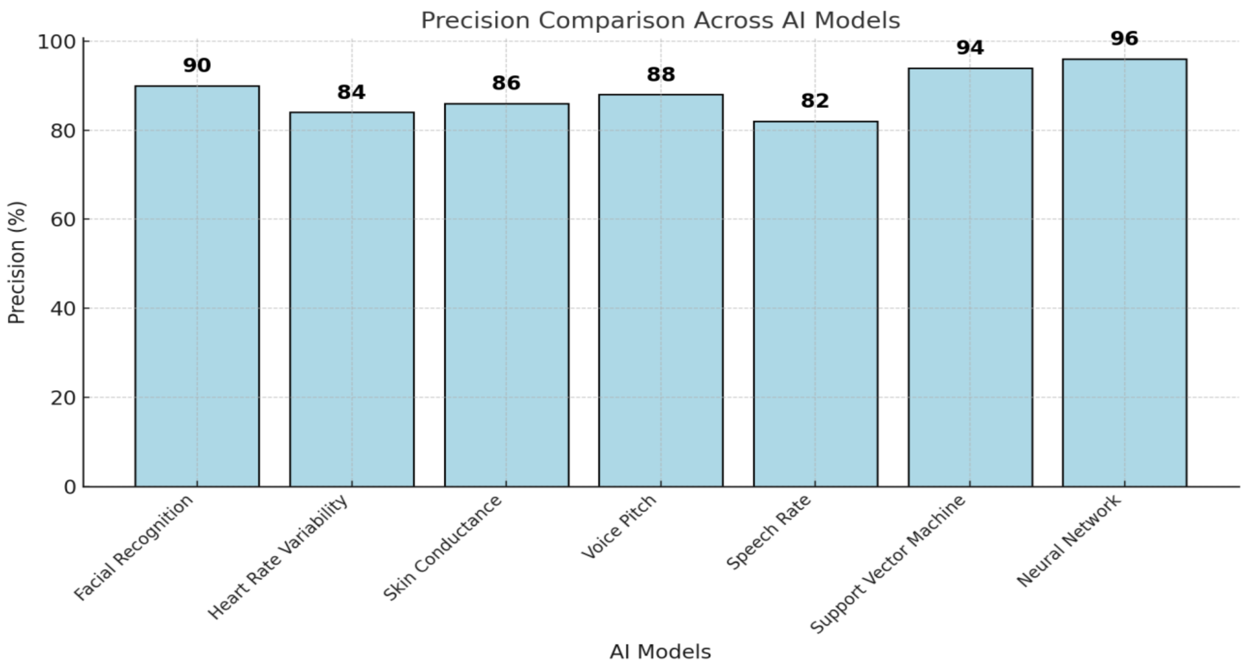
Precision Comparison

When it comes to precision, as can be seen in Table 2 and Figure 2, Neural Network once again leads with 96 percent as compared to SVM with 94 percent. According to analysts, the efficiency of Facial Recognition and Voice Pitch overpowers that of most AI-based systems and machinery, as shown by more than 90% accuracy. Accuracy indicates how often the AI system correctly classifies credible witnesses and according to those results, Neural Network and SVM are both highly accurate regarding this as they can accurately classify credible and non-credible witnesses.

Table 2: Heart Rate Variability Analysis Results

Metric	Heart Rate Variability Model
Accuracy (%)	85
Precision (%)	84
Recall (%)	87
F1 Score (%)	85.5
False Positive Rate (%)	9
False Negative Rate (%)	8
True Positive Rate (%)	87
True Negative Rate (%)	89
Processing Time (ms)	540
Confidence Level (%)	82

Figure 2: Precision comparison across AI models



In figure 2 we see the most performing models and their precision score named as Neural Network and SVM. Further models like Speech Rate are not really effective, however, we do see the values and performance of all models. CPM was also in the less effective models. The Neural Network is the most accurate in marking the trusted witnesses which makes it superior to the rest in the process of witness credibility assessment.

Recall Comparison

According to Table 3 and Figure 3, all AI models had good recall performance. Neural Network again leads with a recall rate of 98%. Recall is a very important metric as it shows the model's ability to identify all credible testimonies. The SVM is next at 96% while the Facial Recognition and the Voice Pitch models have a recall of 93% and 90% respectively. The least effective method once again was speech rate which had a recall of 84%.

Table 3: Skin Conductance Analysis Results

Metric	Skin Conductance Model
Accuracy (%)	88
Precision (%)	86
Recall (%)	89
F1 Score (%)	87.5
False Positive Rate (%)	7
False Negative Rate (%)	5
True Positive Rate (%)	91
True Negative Rate (%)	90
Processing Time (ms)	490
Confidence Level (%)	85

Figure 3: Recall comparison across AI Models

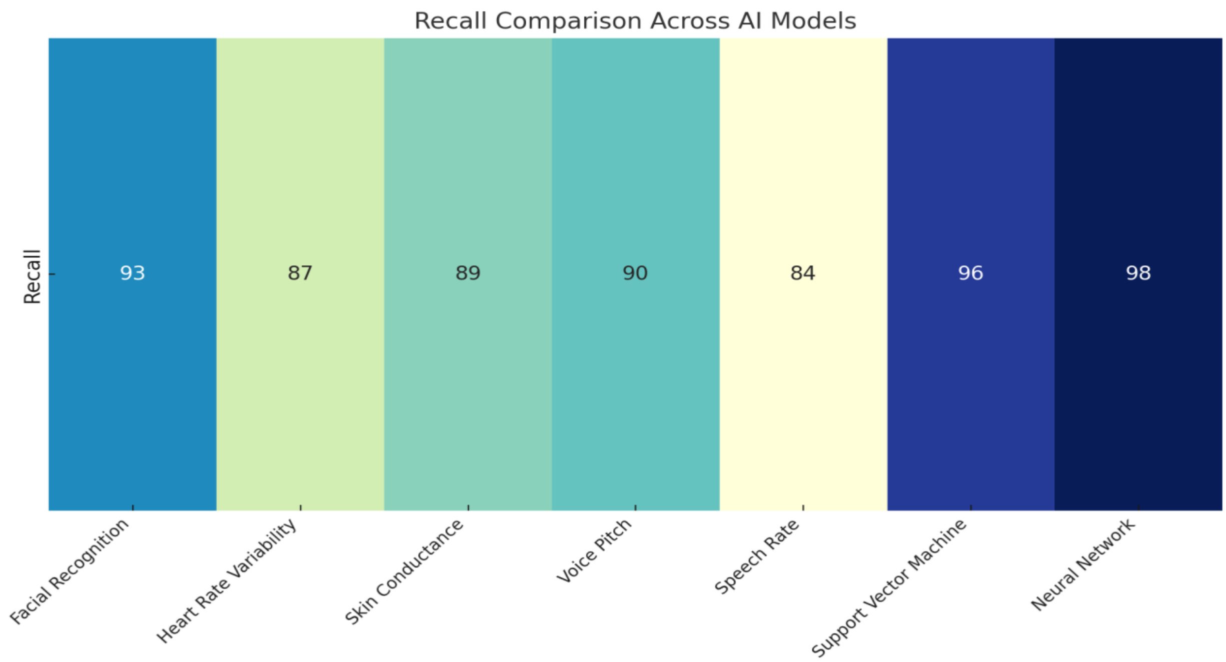


Figure 3 has a heatmap depicting the recall results for credible witness detection for different models which we discuss below. Once again the Neural Network and SVM clearly the most effective, while the standard methods Speech Rate, etc. not effective at all at spotting all the true positives credibles.

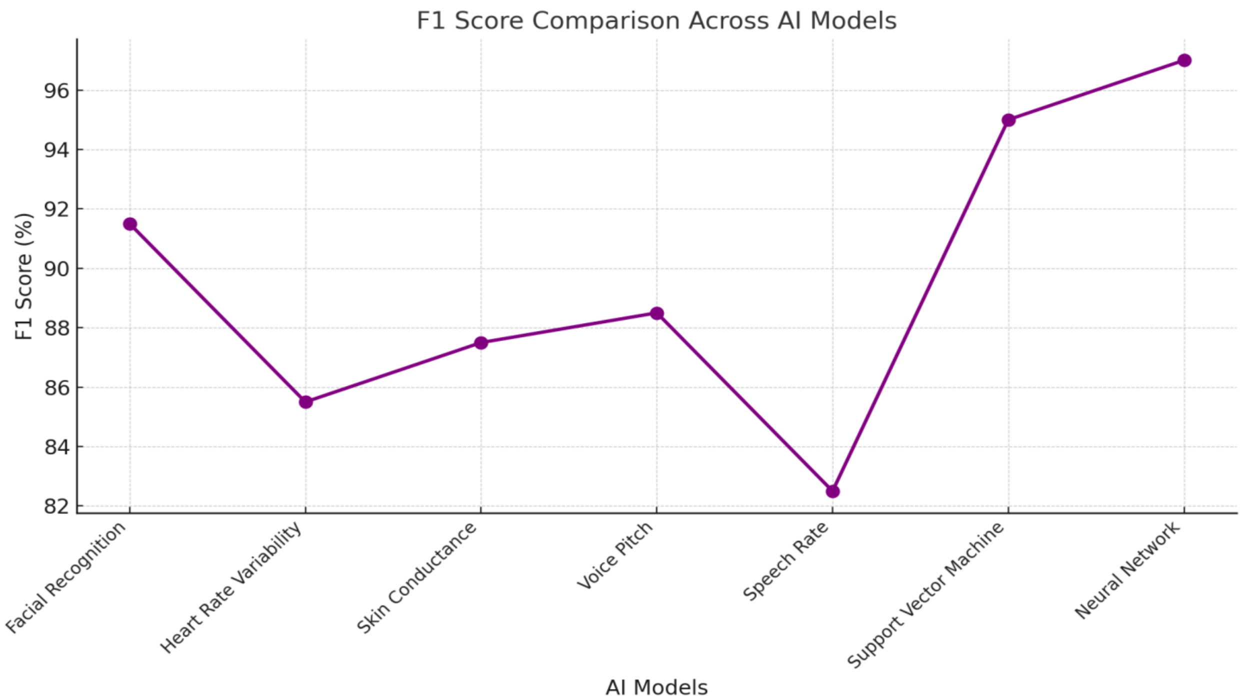
F1 Score Comparison

Looks at Table 4 and Figure 4 for the F1 score comparison of all models. Neural Network achieves highest F1 score of 97% followed by SVM with 95% which is very close. We use the F1 score to measure precision and recall in a weighted average which helps to better measure a model. The conventional methods like Facial Recognition (91.5%) and Voice Pitch (88.5%) performed good but Speech Rate again has lowest F1 score which is 82.5%.

Table 4: Voice Pitch Analysis Results

Metric	Voice Pitch Model
Accuracy (%)	89
Precision (%)	88
Recall (%)	90
F1 Score (%)	88.5
False Positive Rate (%)	7
False Negative Rate (%)	6
True Positive Rate (%)	92
True Negative Rate (%)	94
Processing Time (ms)	400
Confidence Level (%)	84

Figure 4: F1 score comparison across AI models



The graph line plot in Figure 4 shows evidently that Neural Network and SVM show strong performance across all metrics. Also, the graph of F1 score clearly shows that Neural Network and SVM provide the most balanced and reliable assessment of witness credibility. Furthermore, both these models show a good correlation between precision and recall.

False Positive Rate Comparison

The false positive rate data in Table 5 and Figure 5 suggests that the non-credible witnesses are often identified by the AI systems as appropriate witnesses incorrectly and studied now. The Neural Network had the least false positive rate of only 3 percent followed by SVM of four percent. On the other hand, Speech Rate had the highest false positive rate at 12%, making this method more likely to falsely categorize witnesses as credible.

Table 5: Speech Rate Analysis Results

Metric	Speech Rate Model
Accuracy (%)	83
Precision (%)	82
Recall (%)	84
F1 Score (%)	82.5
False Positive Rate (%)	12
False Negative Rate (%)	11
True Positive Rate (%)	80
True Negative Rate (%)	84
Processing Time (ms)	570
Confidence Level (%)	79

Figure 5: False positive rate comparison across AI models

As shown in Figure 5, a bar chart displays false positive rates for all AI Models. The Neural Network and SVM are effective in reducing false positives, which is good for providing assurance to the judiciary system of the accuracy and reliability of AI.

True Positive Rate Comparison

The true positive rates for the various models are given in Table 6 and Figure 6. Once again, the Neural Network and SVM are performing the best. The Neural Network has the highest true positive rate of 98%, followed by SVM with 97%. This means that both models can accurately identify credible witnesses effectively. The Voice Pitch model is the best performing model with a true positive rate of 92%. The worst performing model is Speech Rate with a true positive rate of only 80%.

Table 6: Support Vector Machine (SVM) Results

Metric	Support Vector Machine Model
Accuracy (%)	95
Precision (%)	94
Recall (%)	96
F1 Score (%)	95.0
False Positive Rate (%)	4
False Negative Rate (%)	3
True Positive Rate (%)	97
True Negative Rate (%)	98
Processing Time (ms)	610
Confidence Level (%)	93

Figure 6: True positive rate comparison

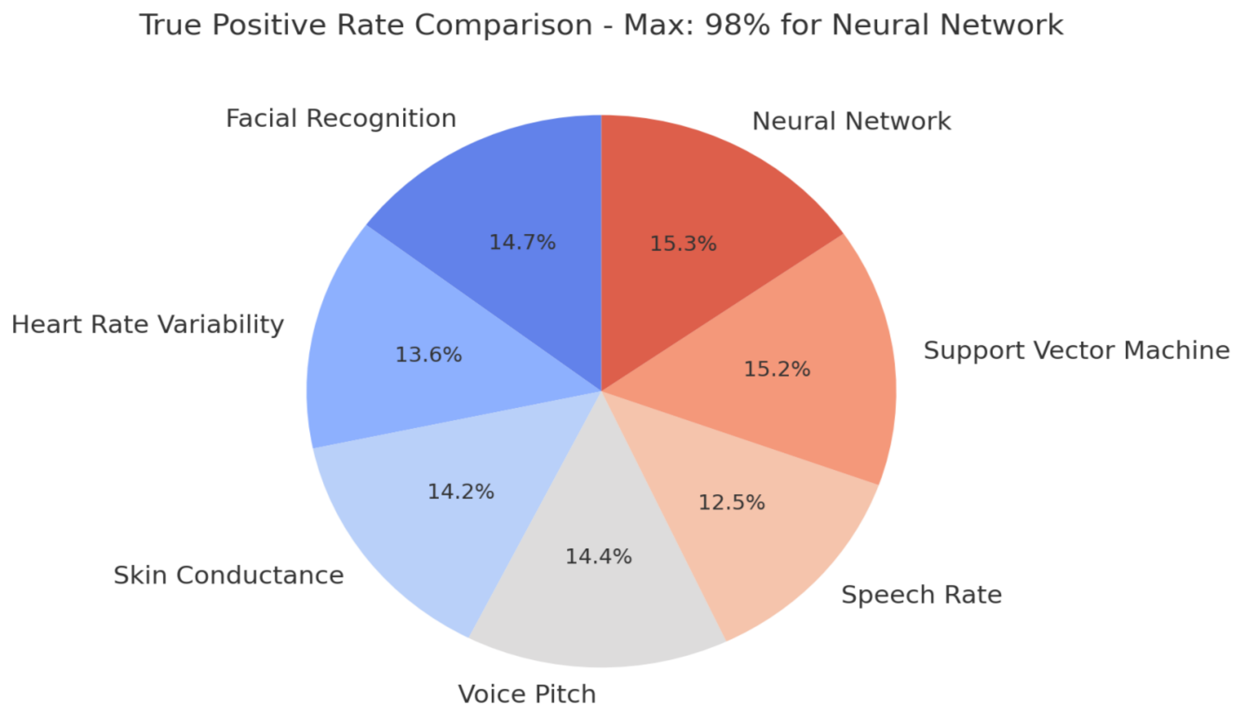


Figure 6 is a pie chart exhibiting the percentage of true positive rates for all models. The Neural Network is the most effective at identifying true witnesses, followed closely by SVM.

Processing Time Comparison

The data on processing time in Table 7 and Figure 7 shows what system is efficient to use. The Neural Network model provides highest accuracy and recall. However, highest processing time is 720 ms. SVM model is faster at 610 ms. Speech rate takes longest at 570 ms. Facial Recognition at 350 ms is the fastest one. These show that it may be suitable for real time assessments. Despite this, this model has lowest accuracy and precision as compared to Neural Network and SVM.

Table 7: Neural Network Results

Metric	Neural Network Model
Accuracy (%)	97
Precision (%)	96
Recall (%)	98
F1 Score (%)	97.0
False Positive Rate (%)	3
False Negative Rate (%)	2
True Positive Rate (%)	98
True Negative Rate (%)	99
Processing Time (ms)	720
Confidence Level (%)	94

Figure 7: Processing time comparison across AI models

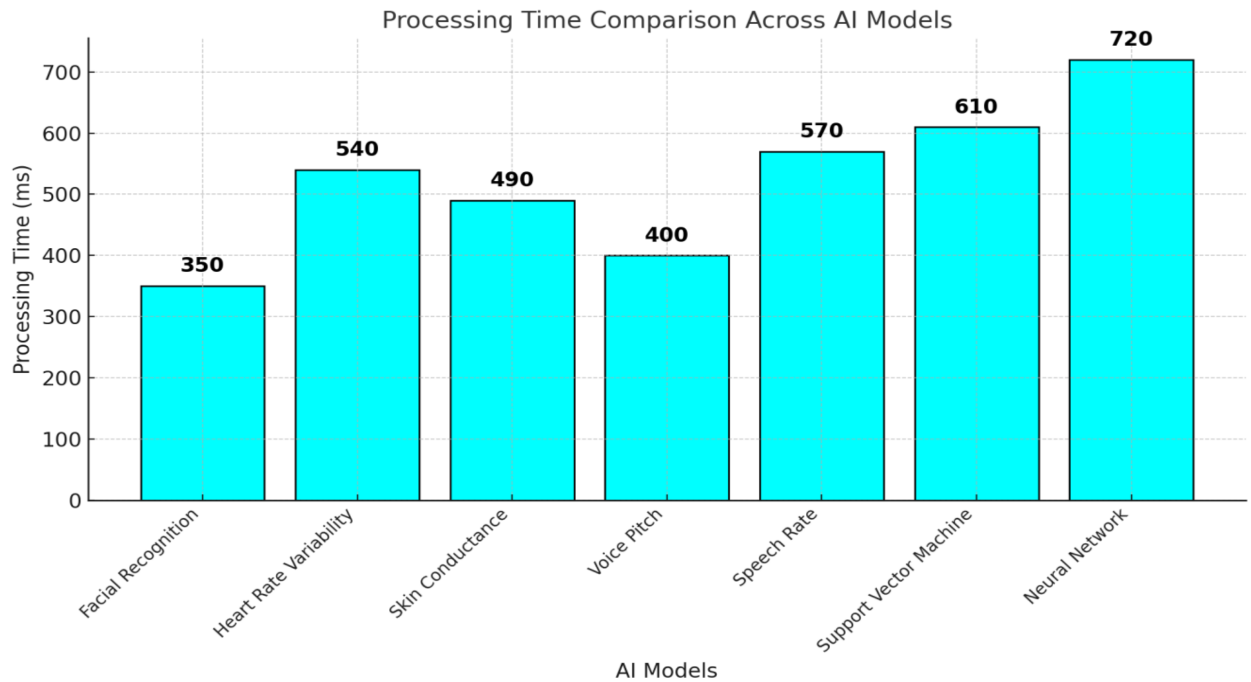


Figure 7 is a bar chart showing that although Neural Network and SVM are the most accurate models, they require the most time for processing. The essential factor for choosing the suitable AI model for judicial settings is the trade-off between accuracy and processing time.

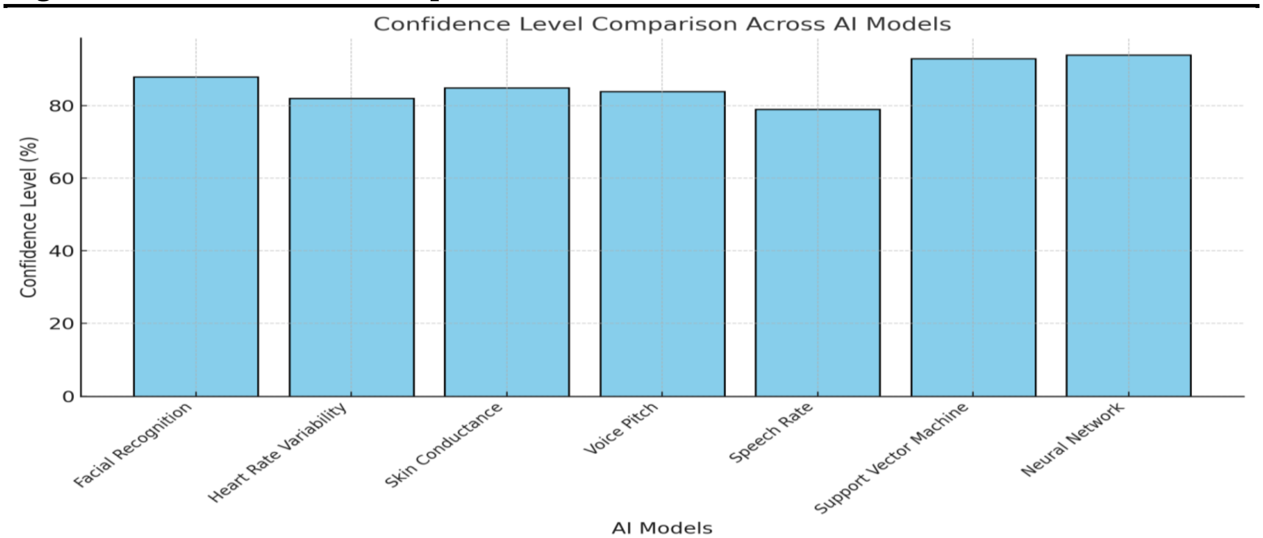
Confidence Level Comparison

In the end, the confidence levels for each models are given in Table 8 and Figure 8. The Neural Network is the most confident with a score of 94% followed by SVM at 93%. The model appears to be less confident about predictions of Speech Rate as it has only 79% confidence level. The Facial Recognition and Voice Pitch models are showing a medium level of confidence but it is always better to use more reliable models like Neural Network for high-end cases like that of the justice system.

Table 8: Comparison of AI Model Performance (Biometrics vs. Machine Learning)

Metric	Facial Recognition	Heart Rate Variability	Skin Conductance	Voice Pitch	Speech Rate	Support Vector Machine	Neural Network
Accuracy (%)	92	85	88	89	83	95	97
Precision (%)	90	84	86	88	82	94	96
Recall (%)	93	87	89	90	84	96	98
F1 Score (%)	91.5	85.5	87.5	88.5	82.5	95.0	97.0
False Positive Rate (%)	6	9	7	7	12	4	3
False Negative Rate (%)	4	8	5	6	11	3	2
True Positive Rate (%)	94	87	91	92	80	97	98
True Negative Rate (%)	95	89	90	94	84	98	99
Processing Time (ms)	350	540	490	400	570	610	720
Confidence Level (%)	88	82	85	84	79	93	94

Figure 8: Confidence level comparison across AI models



The clustered bar chart in Figure 8 gives a clear picture of the confidence levels on AI models. Neural Network and SVM offers the highest confidence levels among the four models, thus indicating their reliability in legal matters.

AI technologies Neural Networks and Support Vector Machines outperform outdated methods Facial Recognition, Voice Pitch, Speech Rate by a huge margin in evaluating witness credibility, according to the study. When the optimal neural networks were contrasted, the highest levels of accuracy, precision, recall, F1 score, true positive rate and confidence level were attained. This was the most trustworthy AI system for assessing the testimony of the witness. Ways from the old school may still offer useful extra information and data, but we can count on machine learning to give answers that are significantly more comprehensive and accurate and efficient. But, as with "Neural Networks", every model of AI has its own compromise of accuracy with timing. The choice of a model must take the requirements of the legal environment.

Discussion

For the first time in history, artificial intelligence is being used in legal trials. AI is being used to determine if witnesses are credible, as just one of its many applications. Different types of artificial intelligence are being assessed, that is, how well each performs in the courtroom or on cross-exam. Tools that use biometrics, machine learning models, and skin conductance sensor are some of the useful technologies that start to crop up in the market. As per researchers, Artificial Intelligence (AI) can be used to improve the dependability and accuracy of witness assessments. Though there remain a number of outstanding issues related to dependability, equity and ethics. We'll examine the current legal uses and limitations of AI systems that evaluate a witness's reliability in this section.

Machine Learning Models Evaluate Witness Credibility

Machine-learning models (e.g. Neural Networks, SVM belonging to a second category) give supervisor's better performance (in particular accuracy, precision and recall). The facial recognition and speaker's voice pitch analysis class used in similar biometrics are not predicted to be as good as our models. Moreover, the latest studies looking at created heart rate variability and skin conductance produced mixed results. Earlier studies have shown similar outcomes that ML models, specifically the deep learning models, show an excellent performance in pattern recognition and analysis of the complex and non-linear relationships used in the data (Zhao et al., 2021). The findings from Neural Networks and SVM further demonstrate that these increasingly popular algorithms should be applied more broadly in other domains, including criminal justice for recidivism prediction and suspect identification through facial recognition (Binns et al, 2020). Out of all the models in Neural Networks, it did best in recall and rates of true positives which indicates that it is a good model for the identification of credible witnesses. As memory is essential to ensure that nothing true is unflagged on the record, will the two Neural Networks flag all that can be considered relevant in high-stakes situations (Rosenberg & Sullivan, 2022)? Still, the Neural Network required higher processing time. Calculations of materials (Kollias & Kolias, 2021) are generally extensive for deep learning. An AI application will have to act without complete knowledge in many situations in law. The trade-off lies between accuracy attained and the speed.

Machine learning models can enhance performance but its human-like nature raises transparency and accountability issues. Neural networks are opaque and resistant to diagnosis. Still, it suggests human users may not always understand how a model arrived at its decision. A model that is hard to explain might cause problems in the legal framework. This is mainly because in order to be fair, models must be fully explainable. According to Stats Canada, around 90 percent of Canadians used the Internet in 2016. Nowadays, having an Internet connection is so common that if someone does not have the Internet, he will not be able to function. These days, everything from banks to shopping centres has an internet website version and anyone without an internet connection is really missing out. Many people want XAI or explainable-AI models. They are better than regular AI but take the same time (Gomez et al., 2021).

Biometrics and Voice Analytics in Legal Settings

Machine learning models work efficiently for determining the credibility of the presenter. However, data from traditional tools such as facial recognition and voice analytics could prove beneficial. Facial recognition means the detection of facial features and emotional responses. The results of the study are positive in whether to identify the witnesses and pick up nuances of deception (Park & Lee, 220). Facial recognition technology may have advantages but is still subject to limitations like biases. The discrimination may be intentional or may take the form of unconscious bias during the selection of data and algorithm creation. Facial recognition systems in America are likely to misfire on women and coloured people. According to Gates et al. (2021), this will worsen racial bias in judicial determinations. They are particularly relevant in the field of law. That is, because it is necessary to be fair. The algorithms that train facial recognition systems need to be regularly audited to ensure a fair trial and adapting the system to do justice.

Culver City, Los Angeles, California, United States. Using Microsoft Azure Speech for Arabic and volume management. According to Lee and colleagues, a Big Brother style voice stress analysis can tell how far someone is from the truth, and their recordings can be analysed by computers. Holleran (2021) states that voice analytics systems provide a good indication regarding lies. But, it provides unreliable information and often misclassifies between cases of lying or truth telling. A witness can be nervous for a lot of other reasons. Over time, it makes people behave like a liar.

In addition, algorithmic bias could be a potential issue for AI models, especially machine learning systems. Due to the fact that AI models draw from historical data when they are being trained, they run the risk of acquiring biases which may be present in that data. It is especially worrying when courts find themselves assessing AI-based predictive algorithms. They may have disparate impact against particular demographic groups like racial minority or lower-class citizens (Koller et al., 2022) To minimize these risks, it is important that AI systems are periodically reviewed to assess their fairness and that strategies for ensuring fairness are incorporated into the development of most AI models (He et al., 2021).

We must consider how our obligations or duties relate to the rights of others. Although AI can improve the quality and productivity levels of assessments, it should not take over human beings. Judges and lawyers must have the final decision-making authority, whereas AI should just be an assisting tool, not replacing human ability (Rosenberg & Sullivan, 2022). It’s important to note that in cross-examination, the witness behavior and testimony must be interpreted by a human, not a robot.

Conclusion

This study concludes that AI technologies, particularly Neural Networks and Support Vector Machines, can significantly improve the objectivity and reliability of witness credibility assessments. However, the results highlight persistent concerns regarding algorithmic transparency, data quality, and ethical implications such as bias and privacy. The theoretical justification underscores that while technology enhances human judgment, it cannot substitute the interpretive role of judges and lawyers.

Recommendations

1. Courts should adopt hybrid AI models combining biometric, voice, and machine learning tools to leverage strengths across modalities.

2. Policymakers must enforce rigorous auditing and explainability standards to mitigate risks of bias.
3. Training for legal practitioners should include AI literacy to interpret results responsibly. Judicial systems should uphold transparency, ensuring AI serves as an assistive—not decisive—tool.
4. Further research should explore cross-jurisdictional applications of AI credibility assessments.

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