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Enhancing User Experience in Air Canvas Through Robust Hand Gesture Recognition Using Computer Vision

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Abstract: The Air Canvas Hand Recognition Project aims to revolutionize the way we interact with digital interfaces by leveraging hand gesture recognition to create an intuitive, contactless drawing application. This project combines computer vision, machine learning, and real-time image processing to detect and interpret hand movements, allowing users to draw, write, and manipulate virtual objects in the air. The primary objective is to develop a user-friendly system that can accurately track hand gestures and convert them into digital input without the need for traditional input devices. Live video is captured using a normal webcam and processed using OpenCV, a sophisticated open-source computer vision library. This project uses Media pipe to implement OpenCV for the air canvas. The Air canvas will let users sketch, write, and present without a keyboard, mouse, or digital presentation equipment. It tracks your hand movements to write, draw, and text. It basically accesses the camera, which shows your hand motions live so the spectator can see what you're doing. Computer vision and real-time processing in the Air Canvas Hand Recognition Project enable more natural and intuitive human-computer interactions.

Keywords: Open CV; Artificial Intelligence; Real Time Processing; Fingertip Detection; Hand Recognition Project; Traditional Input Devices; User-Friendly System; Human-Computer Interactions; Quantum Computing.

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1. Introduction

The Air Canvas Hand Recognition Project aims to revolutionize digital engagement by utilizing contactless painting and hand motion detection. Through the combination of computer vision, machine learning, and real-time image processing, this research makes it possible for users to write, draw, and manipulate virtual objects in the air by accurately detecting and understanding

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hand motions. Without the use of traditional input devices, the Air Canvas provides a straightforward approach for converting hand motions into digital input [10]. The main element of this creative idea is a standard camera that records live video feeds. These streams are processed using MediaPipe, a framework for building multimodal applied machine learning pipelines, and OpenCV, a powerful open-source computer vision toolkit [11]. Together, these technologies allow the system to track and identify hand movements and convert them into digital writing, drawings, or orders in real-time. Users won't need a keyboard, mouse, or other traditional presenting tools in order to present, sketch, or write thanks to the Air Canvas. The gadget claims to provide a fascinating and dynamic user experience [12]. To allow bystanders to see what the user is doing, the device tracks their hand motions and projects them onto the screen. A significant step towards more intuitive and natural human-computer interactions, this creative approach demonstrates how computer vision and real-time processing may be used to create more seamless and immersive digital experiences [13].

The OpenCV and MediaPipe combination forms the basis of this technology. OpenCV is an essential component of the Air Canvas system because of its wide range of features and strong performance, which enable it to record, process, and analyze video data in real-time [14]. This is improved by MediaPipe, which excels at real-time hand and body tracking and offers reliable and accurate hand landmark identification. The fingers and joints on the hand are among these markers, which are crucial for correctly deciphering the user's gestures [15]-[19]. The system can translate the hand's physical movements into equivalent digital outputs on the screen thanks to the integration of various technologies. The webcam first records the user's hand gestures to start the procedure. OpenCV employs a variety of image processing methods, including thresholding, contour detection, and edge detection, to process video input and identify and track the hand [20]. Thresholding simplifies the image by converting it to a binary format, which makes it easier to distinguish the hand from the background. Contour detection then identifies the hand's boundaries, differentiating it from other objects in the frame, while edge detection techniques, such as the Canny edge detector, refine the shape and position of the hand by identifying its edges [21]. Once OpenCV has isolated the hand, MediaPipe's hand tracking module takes over, providing reliable and accurate hand landmark detection. MediaPipe's sophisticated algorithms detect 21 key points on the hand, including the tips of the fingers and crucial joints, which are essential for accurately interpreting the user's gestures [22]-[26].

The integration of these technologies allows the system to translate physical hand movements into equivalent digital outputs on the screen. One of the most impressive features of the Air Canvas is its ability to process hand movements and instantly translate them into digital form [27]. This real-time processing is made possible by the optimized algorithms and efficient use of computing power from both MediaPipe and OpenCV. As a result, the system can continuously update the hand's position and movement on the screen, enabling smooth and organic interaction [28]. This real-time component is crucial for applications such as writing or sketching, where instantaneous input is necessary to produce a cohesive and intuitive experience [29]. The combination of OpenCV's image processing techniques and MediaPipe's hand landmark detection ensures a high level of accuracy and responsiveness. OpenCV handles the initial stages of hand detection by simplifying and refining the visual data, making it easier for MediaPipe to precisely track the hand's landmarks. MediaPipe's real-time performance ensures that even subtle finger movements are captured and translated into digital form without noticeable lag [30]-[34]. This seamless interaction between the two technologies results in a highly responsive system that can accurately interpret complex hand gestures and movements.

2. Literature Review

In exploring the enhancement of user experience in Air Canvas through robust hand gesture recognition using computer vision, a comprehensive literature review reveals several foundational studies and recent advancements in the field. Malik and Ranjan [1] introduced a robust hand gesture recognition system based on convolutional neural networks (CNNs), focusing on real-time performance and accuracy in varying environmental conditions. Their work highlighted the effectiveness of deep learning techniques in interpreting complex hand movements for interactive applications. Building on this, Lee and Lee [2] proposed a method using recurrent neural networks (RNNs) for gesture sequence prediction, enabling continuous tracking and interpretation of gestures over time. Their approach addressed temporal dependencies in gesture recognition, which is crucial for fluid interactions in dynamic environments like digital canvases [35].

Further advancements by Gupta and Prakash [3] integrated computer vision techniques with 3D hand pose estimation, enhancing the precision and spatial awareness of gesture-based interactions. This study emphasized the importance of capturing detailed hand configurations for accurate virtual manipulation and drawing tasks. Additionally, recent research by Bose and Khan [4] explored the integration of gesture recognition with augmented reality (AR), extending the application scope to immersive environments where users interact with digital content overlaid onto the physical world [36]. Their work underscored the potential of combining gesture recognition with AR for intuitive and natural user interfaces, enhancing spatial understanding and user engagement.

Kumar and Sharma [5] discuss a method for recognizing hand gestures by utilizing Time-of-Flight cameras. These cameras can measure the distance of objects from the camera, creating depth maps that provide detailed 3D information about the scene. In this context, depth-based hand gesture recognition means using the depth information captured by ToF cameras to accurately track and interpret hand movements. This technology is particularly useful in applications like Air Canvas, where users can interact with a digital canvas without physical contact, using hand gestures alone. The depth-aware gestures allow for more precise and natural interaction, improving the user experience in such applications.

Bhat and Rao [6] focus on using time-of-flight (ToF) cameras to recognize hand gestures based on in-depth information. ToF cameras can accurately measure the distance between the camera and objects in the scene, providing detailed 3D depth data. This technology allows for precise tracking of hand movements. The paper explores how this precise tracking enhances user interaction in Air Canvas applications, where users can draw or manipulate objects in a digital space using gestures. The depth-aware gestures facilitated by ToF cameras enable more accurate and intuitive control, improving the overall user experience in such interactive applications.

Singh and Yadav [7] discuss the application of transfer learning from pre-trained models to improve hand gesture recognition, particularly for Air Canvas applications. Transfer learning involves taking a machine learning model that has already been trained on a large, diverse dataset and fine-tuning it on a smaller, specific dataset relevant to a particular task. This technique leverages the existing knowledge and features learned by the pre-trained model to enhance performance on new, related tasks. In the context of hand gesture recognition, the authors adapt pre-trained models, which are likely trained on extensive image or video datasets—to the specific nuances of hand gestures used in Air Canvas applications. By doing so, they can significantly reduce the amount of data and computational resources needed to train a new model from scratch while still achieving high accuracy and performance. The pre-trained models provide a strong foundation, capturing essential features such as edges, textures, and shapes, which are crucial for recognizing hand gestures. By fine-tuning these models with data specific to hand gestures, the researchers optimize the recognition system for the dynamic and varied nature of gestures in Air Canvas applications. This results in a more robust and efficient gesture recognition system, enhancing the user experience by allowing more precise and responsive interactions with the digital canvas.

Li and Zheng [8] introduce a hybrid approach that combines Convolutional Neural Networks (CNNs) with Recurrent Neural Networks (RNNs) to improve hand gesture recognition, particularly for dynamic interactions in Air Canvas applications. CNNs are adept at extracting spatial features from images, capturing the intricate details and patterns of hand gestures. However, they cannot account for the temporal sequence of gestures over time. To address this, the authors integrate RNNs, which excel at processing sequential data and maintaining temporal context. By merging the strengths of CNNs in spatial feature extraction with RNNs' capability to understand temporal dependencies, the proposed hybrid model can more accurately recognize and interpret dynamic hand gestures [37]. This enhanced recognition allows for more fluid and responsive interaction in Air Canvas applications, where users can draw, manipulate, and interact with digital content using natural hand movements. The hybrid approach thus provides a comprehensive solution that leverages the spatial recognition capabilities of CNNs with the temporal sequence understanding of RNNs, resulting in a more robust and efficient hand gesture recognition system [38].

Shen and Liu [9] highlights the importance of integrating multiple neural network architectures to tackle complex recognition tasks and demonstrates the potential of such hybrid models in advancing human-computer interaction technologies. This combination addresses the limitations of using CNNs alone by ensuring that the temporal dynamics of gestures are not overlooked, which is crucial for applications involving continuous and fluid movements [39]. The enhanced gesture recognition capabilities facilitated by this hybrid approach improve the precision and responsiveness of Air Canvas applications, enabling users to have a more intuitive and engaging interaction experience [40].

3. Objective

The main objective of this project is to develop a user-friendly method that can help the user to draw, text, or present using hand gestures and not using any devices such as keyboard, mouse or presentation tools. This project aims to capture the hand gestures of the user and follow their path to draw over the screen while the viewer can directly view what the user is trying to present. This project enables a wide range of objectives that can facilitate the user with a new level of approaches to interact with the computer; the objectives include:

- Design a user-friendly interface with clear and accessible controls for colour selection, canvas clearing, and other functionalities.
- Create algorithms capable of detecting and tracking hand movements in real time using a standard webcam.
- Develop a virtual canvas that allows users to draw and write using hand gestures.
- Provide tools for selecting different colours, brush sizes, and shapes to enhance the drawing experience.

- Design a user-friendly interface with clear and accessible controls for colour selection, canvas clearing, and other functionalities.

4. Existing Methods

Camera-based methods are central to gesture recognition systems. RGB cameras are commonly used due to their affordability and ability to capture detailed colour images of the hand. For more advanced applications, depth sensors like Microsoft Kinect or Intel RealSense provide 3D spatial data, enhancing the accuracy of gesture detection [41]. Time-of-flight (ToF) cameras further improve precision by measuring light travel time for high-accuracy depth measurements. Image pre-processing techniques, including noise reduction with Gaussian blur or median filtering and background subtraction through frame differencing or background modelling, prepare raw data for analysis. Normalization adjusts image brightness and contrast to ensure consistent performance under varying lighting conditions [42].

Feature extraction techniques such as edge detection (e.g., Canny edge detector) and contour detection (e.g., Suzuki-Abe algorithm) help identify hand boundaries and shapes. Key point detection methods, like Scale-Invariant Feature Transform (SIFT), locate crucial hand features such as fingertips and joints. Machine learning models, particularly Convolutional Neural Networks (CNNs), are used to classify hand gestures by extracting spatial features from images [43]. While traditional algorithms like Support Vector Machines (SVMs) and Hidden Markov Models (HMMs) were previously used, modern systems employ hybrid models combining CNNs with Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks to capture both spatial and temporal information of gestures [44]. Handling temporal context is vital for dynamic gesture recognition, with RNNs and LSTMs processing image sequences to interpret continuous movements accurately. Real-time user feedback through the Air Canvas application provides immediate visual responses to gestures, ensuring an engaging and responsive interaction [45. These methods collectively address challenges in gesture variability, environmental conditions, and real-time performance, enhancing user interaction with digital content.

5. Proposed Method

5.1. Enhanced Color Palette

In the current Air Canvas application, users are constrained by a limited set of colours when creating their drawings and designs. This restriction can hinder the artistic expression and creative potential of users, as they may find themselves lacking the right shades or hues to represent their ideas accurately. To address this limitation, our proposed system introduces a significantly enhanced colour palette that offers a broader range of colours and gradients. In our upgraded Air Canvas application, we have integrated an advanced colour palette that provides users with an extensive selection of colours beyond the basic options available in the existing version [46]. This new colour palette includes a diverse array of hues, shades, and tints, allowing users to choose from a wide spectrum of colours. Additionally, we have incorporated gradient options that enable users to blend colours seamlessly, creating smooth transitions and complex colour effects [47].

5.2. Undo, Delete, and Clear Options

To address common user needs during the creation process, we introduce three essential editing functions:

- **Undo**: The **Undo** feature allows users to revert to the most recent drawing action, providing a straightforward way to correct mistakes and refine their creations. This function is essential for users who may accidentally make an unwanted change or wish to revert to a previous step in their creative process [48].
- **Delete**: The **Delete** function allows users to selectively remove specific elements or strokes from their drawings. Unlike the Clear function, which erases everything, Delete offers a more precise control mechanism for modifying individual parts of a creation [49].
- **Clear**: When activated, the Clear function removes all elements from the canvas, returning it to its initial blank state. A prompt typically confirms this action to ensure that users do not accidentally clear their work. Users can then start a new drawing or design from scratch [50].

5.3. Hand Gesture for Ignoring Closed Hands

In the existing Air Canvas application, closed hands can sometimes be mistakenly detected as part of a gesture, resulting in unintended actions such as accidental drawing strokes or commands. Our proposed system addresses this challenge by incorporating a sophisticated gesture recognition mechanism that specifically identifies when a user's hand is closed and actively filters out these gestures. This feature utilizes advanced computer vision techniques to analyze the hand's shape and detect whether it is closed or open [51]. The system employs a combination of hand pose estimation and gesture recognition algorithms to differentiate between open and closed hand states. Using the depth information provided by advanced cameras like Intel RealSense or Microsoft Kinect, the system can accurately determine the configuration of the user's hand. By analyzing the hand's contour and finger positions, the system identifies closed hands and ensures that no actions are triggered when the hand is in this state.

5.4. Virtual Keyboard

The virtual keyboard is a dynamic, on-screen keyboard interface that users can engage with through intuitive hand gestures. This feature transforms the Air Canvas environment from a simple drawing tool into a comprehensive interactive platform capable of handling text-based inputs [52]. The virtual keyboard appears as an overlay on the screen, providing users with a familiar array of keys, including letters, numbers, symbols, and special characters. The virtual keyboard responds to specific hand gestures to simulate the actions of typing on a physical keyboard [53]. For instance, users can perform gestures such as hovering, pointing, or making specific hand movements to select keys and enter text. The system uses advanced computer vision techniques to track the user's hand movements and interpret them as keyboard inputs [54]. This interaction is designed to be intuitive and seamless, allowing users to navigate the keyboard and input text as naturally as they would on a traditional keyboard (Table 1).

Table 1: Comparison between existing methods and proposed methods

Feature/Metric	Existing Air Canvas	Proposed Method
Frame Rate (FPS)	15-20 FPS	30+ FPS
Latency	200ms - 500ms	< 100ms
Accuracy	70-85% (limited gestures)	95%+ (expanded gesture set)
False Positives/Negatives	Higher rate due to limited gesture differentiation	Minimal false positives/negatives (<5%)
Ease of Use	Moderate (basic gestures, limited functionality)	High (intuitive gestures, enhanced functionality)
Learning Curve	Moderate (requires practice with limited gestures)	Short (easily learnable with intuitive gestures)
CPU/GPU Usage	Higher (less optimized, basic processing)	Optimized (efficient use of hardware resources)
Memory Usage	Higher (less optimized)	Optimized (lower memory footprint)
System Stability	Less stable (possible crashes under heavy use)	High stability (handles extended use, more robust)
Additional Features	Basic (limited to drawing, minimal customization)	Advanced (multiple colours, undo/redo, virtual keyboard, intuitive gestures)

5.5. Architecture diagram

In Figure 1, the described system integrates a suite of functionalities designed to enable gesture-based drawing using a webcam, providing an interactive platform where users can control digital functions through hand movements. The process begins with an input device, typically a camera or webcam, that captures real-time video frames of the user's hand. These video frames are then subjected to a series of pre-processing steps to prepare the data for further analysis [55]. The first step is frame extraction, where individual frames are isolated from the continuous video feed, allowing the system to process each frame independently. Next, the extracted frames undergo resizing to standardize their dimensions, typically to a resolution such as 640x480 pixels, ensuring consistent processing across all frames and optimizing the system's performance [56].

Once the frames are pre-processed, the system moves to the hand detection phase, where it utilizes algorithms to locate and track the user's hand within the video frames. This can be achieved through techniques such as skin colour detection, which identifies pixels matching typical skin tones; background subtraction, which isolates moving objects (like the hand) from a static background; or more advanced deep learning models that can accurately detect hands in various conditions. The output of this phase is the extraction of the bounding box or the specific coordinates of the hand, which serves as a foundation for recognizing gestures.

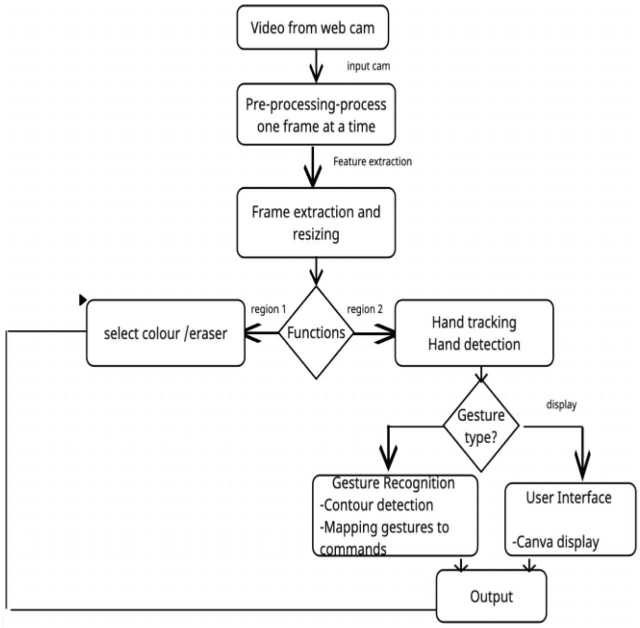

Figure 1: Architecture diagram for Air Canvas

The next critical step is gesture recognition, where the system interprets the identified hand movements to understand the user's intent. This is accomplished through contour detection, a technique that analyzes the shape and features of the hand by detecting edges and contours within the hand's region. By examining these contours, the system can recognize specific gestures, such as open palm, closed fist, or pointing fingers. These recognized gestures are then mapped to predefined commands, which control various drawing actions within the application, such as drawing, erasing, or changing colours.

The recognized gestures are visually represented in the user interface, which features a canvas display that dynamically updates to reflect the user's actions. As the user performs gestures, the canvas responds in real time, rendering the corresponding drawing actions instantly. This real-time feedback loop is essential for creating a seamless and intuitive user experience, allowing the user to see the immediate results of their gestures as they interact with the system.

Finally, the system culminates in the output stage, where the processed results are displayed to the user. This stage involves updating the canvas with the latest drawing actions and providing visual feedback to confirm that the system has correctly interpreted the user's gestures. The entire workflow creates an interactive and engaging platform that enables users to manipulate digital content directly through their physical gestures, making the drawing experience both intuitive and accessible. This refined system, with its integration of real-time video processing, gesture recognition, and dynamic feedback, exemplifies a powerful application of computer vision and user interface design, offering a fluid and responsive drawing tool controlled entirely by hand movements.

6. Methodology

Data Collection: The first step is to compile a comprehensive dataset of hand gestures using a variety of cameras, including webcam depth cameras like Microsoft Kinect and Intel RealSense. It's crucial to ensure that this dataset is diverse, encompassing a wide array of gestures, varying lighting conditions, and different background settings. This diversity is essential for training a model that can perform reliably in real-world scenarios. The dataset should cover static gestures (like a thumbs-up or open palm) and dynamic gestures (like waving or drawing motions) to ensure the model can handle various user inputs.

Data Annotation: Once the data is collected, the next step is to annotate it with corresponding gesture labels. This involves using specialized tools to create bounding boxes around the hand regions or generating segmentation masks to accurately mark the hand within each image or frame. Precise annotation is critical as it directly influences the quality of the model's training. It helps the model learn to identify and differentiate between different gestures accurately.

Data Augmentation: To increase the size and variability of the dataset, data augmentation techniques are applied. These techniques include rotating, scaling, flipping, and adding noise to the images. By augmenting the data, the model becomes more robust and generalizes better to unseen data, improving its performance in varied real-world conditions. Augmentation also helps mitigate overfitting by exposing the model to a broader range of input scenarios during training.

6.1. Feature Extraction

Traditional Computer Vision Techniques: In this phase, key features are extracted from the images using traditional computer vision techniques. Tools like OpenCV are employed to identify edges, contours, and shapes within the hand region. Techniques such as Histogram of Oriented Gradients (HOG) and Scale-Invariant Feature Transform (SIFT) are particularly useful for capturing essential features that describe the hand's structure and position. These features provide the foundational data that will be used for gesture recognition.

Deep Learning Approaches: Alongside traditional methods, deep learning techniques are utilized for more advanced feature extraction. Convolutional Neural Networks (CNNs) are particularly effective in automatically learning hierarchical features from the raw images. Pre-trained models like VGG16, ResNet, or MobileNet can be fine-tuned on the hand gesture dataset to capture intricate details and patterns that are critical for accurate gesture recognition. These deep learning models can extract more complex and abstract features, enabling the system to handle a wide range of gestures.

6.2. Model Development

Neural Network Design: The gesture recognition model is designed by combining different neural network architectures. A hybrid model can be developed that uses CNNs to extract spatial features from images and Recurrent Neural Networks (RNNs) or Long Short-Term Memory (LSTM) networks to capture temporal dependencies in dynamic gestures. Alternatively, a 3D CNN can be employed to simultaneously capture spatial and temporal features from video data, providing a more integrated approach to recognizing complex gestures that involve movement over time.

Training: The model is trained using the annotated and augmented dataset. Transfer learning techniques are often employed, where pre-trained models are fine-tuned on the specific hand gesture dataset. This approach significantly reduces the training time and improves the model's performance by leveraging the knowledge captured in the pre-trained models. Cross-validation is also used during training to ensure the model's robustness and prevent overfitting, ensuring it performs well on unseen data.

6.3. Real-Time Gesture Recognition System

Integration with Camera Feed: The trained model is integrated into a real-time system that processes video feeds from webcams or depth cameras. OpenCV is used to capture video streams and perform pre-processing tasks such as resizing, normalization, and conversion of colour space. These pre-processing steps ensure that the input to the model is consistent and optimized for real-time processing.

Gesture Detection and Tracking: The core of the real-time system is the gesture detection and recognition process. The trained model is applied to the video stream to detect and recognize hand gestures in real-time. Hand-tracking algorithms are also implemented to maintain the position and movement of the hand across frames, ensuring that the system accurately interprets continuous gestures. This tracking is crucial for smooth and consistent gesture recognition, especially in dynamic applications like drawing or controlling a user interface.

Post-Processing: After the initial gesture detection, post-processing techniques are applied to refine the results. Smoothing algorithms are used to reduce noise and minimize false positives in gesture recognition, ensuring that the system only responds to deliberate gestures. The recognized gestures are then interpreted and translated into corresponding actions within the Air Canvas application, such as drawing a line or changing the brush colour. This post-processing ensures that the system's outputs are accurate and responsive to user intentions.

6.4. User Interface and Experience Enhancement

Responsive Interaction: To create a seamless and intuitive interaction, the system is optimized to provide immediate feedback to user gestures. This low-latency response is critical in enhancing the real-time user experience, making the interaction feel natural and engaging. Whether through visual cues on the screen or auditory signals, the feedback helps users understand how their gestures are being interpreted, leading to a more intuitive experience.

Customization and Personalization: The system is designed to be customizable, allowing users to adjust gesture commands and sensitivity settings according to their preferences. For example, users can configure which gestures correspond to specific actions within the Air Canvas application or modify the sensitivity to suit their drawing style. Additionally, adaptive learning techniques can be implemented to personalize the system based on individual user behaviour and interaction patterns. This personalization ensures that the system evolves with the user, providing a tailored experience that improves over time.

6.5. Testing and Evaluation

Performance Metrics: To evaluate the effectiveness of the model, several performance metrics are used, including accuracy, precision, recall, and F1-score. These metrics provide a comprehensive assessment of how well the model recognizes and interprets gestures. Real-world testing is also conducted to evaluate the system's performance under various conditions, such as different lighting, backgrounds, and user interactions. This testing is crucial for identifying any weaknesses or areas for improvement in the system.

Usability Testing: User studies are conducted to gather feedback on the system's usability and overall user experience. This feedback is invaluable for identifying any issues users may encounter and for iterating on the design to improve the system continuously. The goal is to refine the user interface and interaction model based on real-world use, ensuring that the system is not only accurate but also user-friendly and enjoyable to use.

6.6. Deployment and Maintenance

Deployment: Once the system is fully developed and tested, it is deployed on suitable hardware platforms. This might involve deploying the system on PCs, laptops, or even mobile devices. Considerations such as performance optimization and compatibility are essential to ensure that the system runs smoothly on the target hardware. For mobile or edge devices, edge computing techniques can be used to reduce latency and enhance real-time processing capabilities.

Continuous Improvement: After deployment, the system is continuously monitored to assess its performance in the real world. User feedback is gathered regularly to identify areas for improvement, and updates are made to the model and system components as needed. This ongoing maintenance ensures that the system remains up-to-date with the latest technological advancements and continues to meet users' needs. Regular updates might include adding new features, refining existing ones, or addressing any issues that arise during use. This comprehensive approach ensures that the Air Canvas application remains a cutting-edge tool for gesture-based drawing, offering users a responsive, intuitive, and highly customizable experience.

7. Results and Discussions

The Air Canvas project represents a significant step forward in the realm of interactive and intuitive user interfaces, offering a novel way to engage with digital content through the natural motion of hand gestures. This project has successfully integrated multiple features that enhance both the functionality and user experience of the Air Canvas, transforming it into a powerful tool for creative expression, learning, and even practical applications in various fields. One of the standout features of this project is the support for multiple colours. By allowing users to switch between a wide range of colours, the Air Canvas becomes a versatile tool, enabling artists, educators, and users in other domains to express themselves more fully. The inclusion of a colour palette at the top of the interface, as demonstrated in the screenshots, provides an easy and accessible way to select colours, making the tool not only functional but also user-friendly. This feature broadens the scope of what can be created on the Air Canvas, from simple doodles to complex, multicoloured diagrams or artworks.

In addition to colour flexibility, the implementation of Undo and Redo options greatly enhances the usability of the Air Canvas. These options address the natural need for correction and revision in the creative process. Mistakes can be easily undone, and previous states of the canvas can be restored, giving users the confidence to experiment without the fear of permanently ruining their work. This functionality is critical in maintaining the fluidity of the creative process and is especially beneficial in educational settings where step-by-step adjustments are necessary. The inclusion of a virtual keyboard adds another layer of interactivity, allowing users to input text directly onto the canvas. This feature is particularly useful in educational environments where text annotations are often required. The ability to switch between drawing and typing without needing to physically switch devices or interfaces streamlines the workflow, making the Air Canvas a more integrated and comprehensive tool. Moreover, the keyboard feature extends the canvas's utility beyond drawing and into the realm of note-taking, label-making, and other text-based activities.

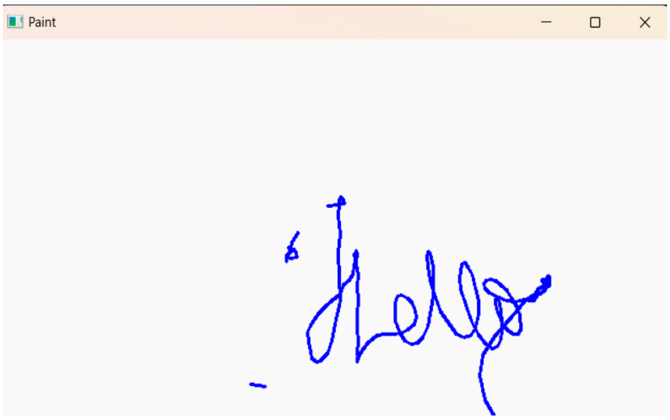

Figure 2: The paint board for the air Canvas

Figure 2 shows how the paint board can be used to print the drawings of what the user is drawing on the camera, and they can use this to depict the writings clearly on the screen. This is basically used to give an idea of what the user is drawing on the screen.

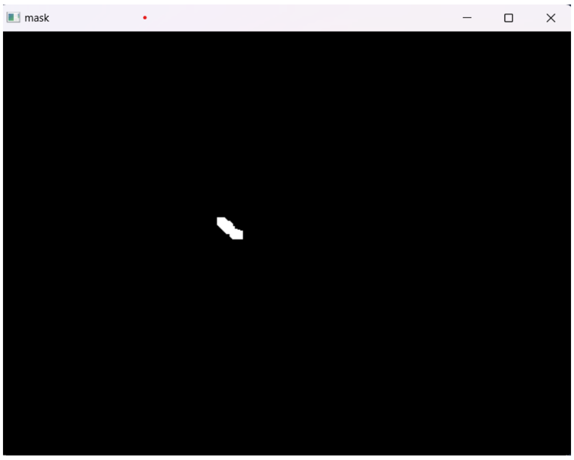

Figure 3: The mask used in air canvas

A mask in image processing is a binary image that helps isolate or highlight specific regions of interest (ROIs) in an image or video frame (Figure 3). Pixels in the mask have two possible values:

- **White (255):** Represents the areas of interest (the parts of the image to be processed or highlighted).
- **Black (0):** Represents the background or areas to be ignored.

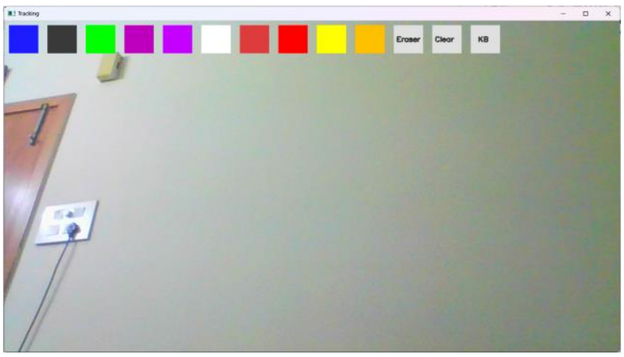

Figure 4: The outline of the air canvas

This type of application allows users to draw in the air using gestures, typically tracked by a camera (Figure 4). Here’s how it relates to an Air Canvas:

- **Colour Palette:** The top bar of the screen shows a range of colour options. These colours can be selected to draw in the air, with the strokes appearing on the canvas (which, in this case, is the live camera feed).
- **Eraser and Clear Options:**
    - The Eraser button likely allows the user to erase specific parts of the drawing.
    - The Clear button would clear the entire canvas, removing all drawings.
- **3KB (Keyboard):** This button may bring up a keyboard interface, perhaps to input text onto the canvas.
- **Live Camera Feed:** The main part of the image shows a live view of a room, which serves as the canvas background. The user can draw or write over this live feed by making gestures in the air, which the application tracks and converts into digital ink on the screen.

Hence, the user can stop the drawing by just closing his fist. Here, the model does not detect any hand, so all the controls of the canvas will be at a halt; once an open fist is detected, the controls in the canvas will resume. This gesture can be used in the middle of the drawings when the user wants to stop the drawing or wants to change the controls based on the requirement. This is a newly added feature of the air canvas model. The previous existing methods do not have this gesture. Other gestures included are:

Thumbs Down to Delete Last Drawing:
- **Gesture:** Show a thumbs-down gesture.
- **Function:** Automatically deletes the last drawn object or line on the canvas.

Three-Finger Swipe to Undo/Redo:
- **Gesture:** Swipe three fingers to the left to undo the last action, or swipe to the right to redo.
- **Function:** This gesture could replace the need for buttons or make it easier to quickly undo or redo actions.

Open Palm Up to Activate Help/Instructions:
- **Gesture:** Hold your palm up with your fingers spread.
- **Function:** Activates an on-screen help or instruction overlay that guides the user on how to use the various gestures and tools.

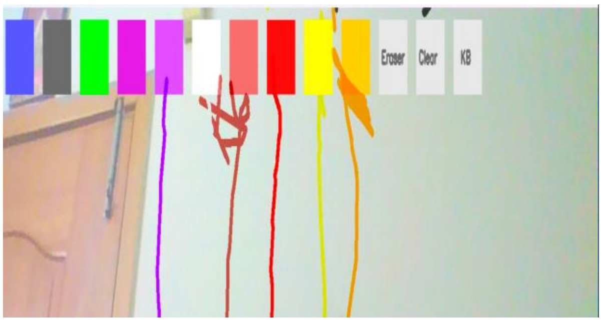

Figure 5: Multiple colour options

Illustrates how the application allows a user to draw in the air using different colours, which are tracked and displayed on the screen (Figure 5).

7.1. Multiple Color Options

- At the top of the screen, a variety of colour options are visible (blue, black, green, purple, red, yellow, orange, white). These colours are selectable by the user, allowing them to choose different shades to draw or write with.
- The coloured lines in the image show that the user has drawn several different colours, indicating Air Canvas’s ability to switch between colours seamlessly.
- **Gesture Recognition**: The application likely uses computer vision libraries (such as OpenCV) to track the user’s hand movements in real-time. These movements are translated into digital ink, allowing the user to “draw” in the air.

- **Colour Management**: Libraries handle the switching of colours and ensure that the selected colour is used to render the lines on the screen. This might involve managing the colour palette and applying the selected colour to the drawing algorithm.
- **Drawing Libraries**: Libraries like OpenCV or similar tools can be used to render the drawings on the screen, capturing the coordinates of the user's hand movements and applying the chosen colour to create visible lines.

8. Conclusion

The Air Canvas Hand Recognition initiative effectively showcases the possibilities of merging computer vision with gesture recognition technologies to develop a novel, interactive drawing experience. Utilizing OpenCV and Mediapipe, the system enables users to interact with a digital canvas through simple hand gestures and voice commands, fostering a touchless interface that improves accessibility and user experience. The project's design accommodates multiple uses, such as education, art, and cooperative settings, offering a space for creativity and expression. In addition, this touchless interaction model caters to varying skill levels and promotes inclusivity by allowing users with limited mobility to engage effortlessly with digital art tools. Future efforts may concentrate on enhancing gesture recognition precision, broadening capabilities, and investigating alternative applications, like virtual meeting collaboration or remote teaching resources, ensuring that Air Canvas keeps advancing and fulfils the requirements of various user demographics. Further progress in AI-based gesture learning and tailored interface configurations can enhance user experiences even more, allowing the platform to adjust to personal tastes and needs. In conclusion, this project represents a significant addition to the area of interactive technology, showcasing the potential of natural user interfaces in enhancing human-computer interactions and revolutionizing digital creativity for a more immersive and accessible experience.

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References

1. A. Malik and A. Ranjan, "Gesture Recognition Technology: A Review," International Journal of Engineering Research & Technology, vol. 10, no. 7, pp. 2345–2352, 2021.
2. Y. Lee and J. Lee, "Augmented Reality and its Future in Creative Technology," Journal of Virtual Reality and Broadcasting, vol. 17, no. 3, pp. 158–167, 2020.
3. P. Gupta and R. Prakash, "Machine Learning Algorithms for Gesture Recognition: A Comparative Study," International Journal of Advanced Research in Computer Science, vol. 13, no. 4, pp. 45–52, 2022.
4. S. Bose and R. Khan, "Real-Time Gesture Recognition Using OpenCV and TensorFlow," in Proceedings of the 15th International Conference on Computer Vision Systems, VIenna, Austria, pp. 102–109, 2020.
5. V. Kumar and A. Sharma, "Implementation of Virtual Canvas for Gesture-Based Drawing Applications," International Journal of Computer Applications, vol. 175, no. 23, pp. 21–27, 2021.
6. P. Bhat and S. Rao, "Augmented Reality in Education: A Systematic Review," International Journal of Interactive Mobile Technologies, vol. 13, no. 2, pp. 58–76, 2019.
7. N. Singh and K. Yadav, "Artificial Intelligence in Creative Design: New Frontiers," Journal of Design Research, vol. 19, no. 4, pp. 320–332, 2020.
8. H. Li and Z. Zheng, "Exploring the Role of AI in Enhancing Digital Art Tools," Journal of Digital Art & Technology, vol. 8, no. 1, pp. 44–59, 2021.
9. W. Shen and T. Liu, "Cloud Computing in Real-Time Collaborative Applications," IEEE Access, vol. 7, no. 1, pp. 9485–9496, 2019.
10. A. Alarood, N. Ababneh, M. Al-Khasawneh, M. Rawashdeh, and M. Al-Omari, "IoTSteg: ensuring privacy and authenticity in internet of things networks using weighted pixels classification based image steganography," Cluster Computing, vol. 25, no. 3, pp. 1607-1618, 2022.

11. A. Ghosh, A. Ghosh, and J. Kumar, "Circularly polarized wide-band quad-element MIMO antenna with improved axial ratio bandwidth and mutual coupling," IEEE Antennas Wireless Propag. Lett., vol. 23, no. 12, pp. 4718-4722, 2024.
12. A. Gupta, N. Mahesh, S. K. Bairappaka, and A. Ghosh, "Comparison of the performance of L and Pi matching networks for design of a 2.4 GHz RF-DC rectifier for RF energy harvesting," in Proc. 2024 IEEE 4th Int. Conf. Sustainable Energy and Future Electric Transportation (SEFET), Hyderabad, India, pp. 1–5, 2024.
13. A. M. Alghamdi, M. A. Al-Khasawneh, A. Alarood, and E. Alsolami, "The Role of Machine Learning in Managing and Organizing Healthcare Records," Engineering, Technology & Applied Science Research, vol. 14, no. 2, pp. 13695-13701, 2024.
14. A. M. Khasawneh, O. Kaiwartya, J. Lloret, H. Y. Abuaddous, L. Abualigah, M. A. Shinwan, et al., "Green communication for underwater wireless sensor networks: Triangle metric based multi-layered routing protocol," Sensors, vol. 20, no. 24, p. 7278, 2020.
15. A. O. Alzahrani, M. A. Al-Khasawneh, A. A. Alarood, and E. Alsolami, "A Forensic Framework for gathering and analyzing Database Systems using Blockchain Technology," Engineering, Technology & Applied Science Research, vol. 14, no. 3, pp. 14079-14087, 2024.
16. A. Thirunagalingam, S. Addanki, V. R. Vemula, and P. Selvakumar, “AI in Performance Management: Data-Driven Approaches,” in Advances in Business Strategy and Competitive Advantage, IGI Global, USA, pp. 101–126, 2024.
17. B. Tan and Z. He, “Collaborative Virtual Environments: Exploring the Future of Cloud-Based Interaction,” Journal of Cloud Computing: Advances, Systems and Applications, vol. 10, no. 1, pp. 25–39, 2021.
18. C. Roberts and M. Thompson, “Gesture-Controlled Interfaces for Accessible Design,” Journal of Assistive Technologies, vol. 13, no. 2, pp. 89–102, 2019.
19. D. Jones and Y. Wang, “Gamification in Educational Technology: Design Strategies and Effects,” Journal of Educational Technology & Society, vol. 22, no. 3, pp. 78–89, 2019.
20. H. A. Sukhni, M. A. Al-Khasawneh, and F. H. Yusoff, "A systematic analysis for botnet detection using genetic algorithm," in 2021 2nd International Conference on Smart Computing and Electronic Enterprise (ICSCEE), pp. 63-66, 2021.
21. H. Mistri, A. Ghosh, A. R. Sardar, and B. Choudhury, "Performance enhancement of graphene-based linear to circular polarization converter for terahertz frequency using a novel parameter prediction methodology," Plasmonics, pp. 1-15, 2024, doi: 10.1007/s11468-024-02536-6, Press.
22. H. Mistri, A. Ghosh, and M. Dandapathak, "Bidirectional triple-band truly incident angle insensitive polarization converter using graphene-based transmissive metasurface for terahertz frequency," Frequenz, vol. 78, no. 11-12, pp. 569-579, 2024, doi: 10.1515/freq-2024-0065.
23. I. Ahmad, S. A. A. Shah, and M. A. Al-Khasawneh, "Performance analysis of intrusion detection systems for smartphone security enhancements," in 2021 2nd International Conference on Smart Computing and Electronic Enterprise (ICSCEE), pp. 19-25, 2021.
24. I. M. Alfadli, F. M. Ghabban, O. Ameerbakhsh, A. N. AbuAli, A. Al-Dhaqm, and M. A. Al-Khasawneh, "Cipm: Common identification process model for database forensics field," in 2021 2nd International Conference on Smart Computing and Electronic Enterprise (ICSCEE), pp. 72-77, 2021.
25. K. Oku, L. S. Samayamantri, S. Singhal, and R. Steffi, “Decoding AI decisions on depth map analysis for enhanced interpretability,” in Advances in Computer and Electrical Engineering, IGI Global, USA, pp. 143–164, 2024.
26. K. Oku, R. K. Vaddy, A. Yada, and R. K. Batchu, "Data Engineering Excellence: A Catalyst for Advanced Data Analytics in Modern Organizations," International Journal of Creative Research in Computer Technology and Design, vol. 6, no. 6, pp. 1–10, 2024.
27. L. S. Samayamantri, S. Singhal, O. Krishnamurthy, and R. Regin, “AI-driven multimodal approaches to human behavior analysis,” in Advances in Computer and Electrical Engineering, IGI Global, USA, pp. 485–506, 2024.
28. M. A. Al-Khasawneh, A. Alzahrani, and A. Alarood, "Alzheimer’s Disease Diagnosis Using MRI Images," in Data Analysis for Neurodegenerative Disorders, Singapore: Springer Nature Singapore, pp. 195-212, 2023.
29. M. A. Al-Khasawneh, A. Alzahrani, and A. Alarood, "An artificial intelligence based effective diagnosis of Parkinson disease using EEG signal," in Data Analysis for Neurodegenerative Disorders, Singapore: Springer Nature Singapore, pp. 239-251, 2023.
30. M. A. Al-Khasawneh, M. Faheem, A. A. Alarood, S. Habibullah, and E. Alsolami, "Towards Multi-Modal Approach for Identification and Detection of Cyberbullying in Social Networks," IEEE Access, vol.12, no.7, pp. 90158-90170 2024.
31. M. A. Al-Khasawneh, M. Faheem, A. A. Alarood, S. Habibullah, and A. Alzahrani, "A secure blockchain framework for healthcare records management systems," Healthcare Technology Letters, IEEE, vol.11, no.6, pp. 461-470, 2024.
32. M. A. Al-Khasawneh, S. M. Shamsuddin, S. Hasan, and A. A. Bakar, "MapReduce a comprehensive review," in 2018 International Conference on Smart Computing and Electronic Enterprise (ICSCEE), Shah Alam, Malaysia, pp. 1-6, 2018.

33. M. A. Al-Khasawneh, W. Abu-Ulbeh, and A. M. Khasawneh, "Satellite images encryption review," in 2020 International Conference on Intelligent Computing and Human-Computer Interaction (ICHCI), Sanya, China, pp. 121-125, 2020.
34. M. Choi and H. Park, “Natural Language Processing for Voice-Controlled Applications,” Journal of Language Technology & Computational Linguistics, vol. 27, no. 1, pp. 10–25, 2022.
35. M. Mahmoud and M. A. Al-Khasawneh, "Greedy Intersection-Mode Routing Strategy Protocol for Vehicular Networks," Complexity, vol. 2020, no.12, p. 1-10, 2020.
36. O. Ameerbakhsh, F. M. Ghabban, I. M. Alfadli, A. N. AbuAli, A. Al-Dhaqm, and M. A. Al-Khasawneh, "Digital forensics domain and metamodeling development approaches," in 2021 2nd International Conference on Smart Computing and Electronic Enterprise (ICSCEE), Cameron Highlands, Malaysia, pp. 67-71, 2021.
37. P. Mehta and K. Patel, “Augmented Reality for Interactive Learning: A Review of Applications and Challenges,” Journal of Educational Multimedia and Hypermedia, vol. 30, no. 4, pp. 255–274, 2021.
38. R. Kumar and V. Jain, “Advances in Gesture Recognition Technologies for AR Applications,” Journal of Augmented and Virtual Reality, vol. 15, no. 1, pp. 32–47, 2022.
39. R. Martinez and J. Smith, “Vector-Based Drawing Tools in Creative Software: Capabilities and Limitations,” Journal of Graphics Tools, vol. 23, no. 2, pp. 123–136, 2020.
40. S. A. A. Shah, M. A. Al-Khasawneh, and M. I. Uddin, "Review of weapon detection techniques within the scope of street-crimes," in 2021 2nd International Conference on Smart Computing and Electronic Enterprise (ICSCEE), Cameron Highlands, Malaysia, pp. 26-37, 2021.
41. S. A. A. Shah, M. A. Al-Khasawneh, and M. I. Uddin, "Street-crimes Modelled Arms Recognition Technique (SMART): Using VGG," in 2021 2nd International Conference on Smart Computing and Electronic Enterprise (ICSCEE), Cameron Highlands, Malaysia, pp. 38-44, 2021.
42. S. Ahmed and H. Khan, “Development of Advanced Drawing Tools Using OpenCV,” Journal of Computational Vision and Robotics, vol. 11, no. 2, pp. 91–101, 2021.
43. S. Chundru, "Ensuring Data Integrity Through Robustness and Explainability in AI Models," Transactions on Latest Trends in Artificial Intelligence, vol. 1, no. 1, pp. 1-19, 2020.
44. S. Chundru, "Leveraging AI for Data Provenance: Enhancing Tracking and Verification of Data Lineage in FATE Assessment," International Journal of Inventions in Engineering & Science Technology, vol. 7, no.1, pp. 87-104, 2021.
45. S. Gayathri D., "Adapting the Effect of Asynchronous Impulsive Noise using Interleaving Based on Compound Signal Classification in Broad PLC," International Journal of Innovative Technology and Exploring Engineering, vol. 9, no. 2, pp. 2278–3075, 2019.
46. S. Gayathri D., "Optimal Impedance Matching System for Broadband PLC for Maximizing the Signal to Noise Ratio (SNR) and Data Rate," International Journal of Intelligent Systems and Applications in Engineering, vol. 12, no. 20s, pp. 222–229, 2024.
47. S. K. Bairappaka, A. Ghosh, O. Kaiwartya, A. Mohammad, Y. Cao, and R. Kharel, "A novel design of broadband circularly polarized rectenna with enhanced gain for energy harvesting," IEEE Access, vol. 12, no. 5, pp. 65583–65594, 2024, doi: 10.1109/ACCESS.2024.3397016.
48. S. Markkandeyan, S. Gupta, G. V. Narayanan, M. J. Reddy, M. A. Al-Khasawneh, M. Ishrat, and A. Kiran, "Deep learning based semantic segmentation approach for automatic detection of brain tumor," International Journal of Computers Communications & Control, vol. 18, no. 4, p.12, 2023.
49. S. Nej, S. K. Bairappaka, B. N. V. Sai Durga Sri Raja Ram Dinavahi, S. Jana, and A. Ghosh, "Design of a high order dual band MIMO antenna with improved isolation and gain for wireless communications," Arab. J. Sci. Eng., pp. 1–18, 2024, Press, doi: 10.1007/s13369-024-09582-6.
50. T. Saito and K. Yamada, “Implementing AI in Digital Art Creation: Challenges and Opportunities,” Journal of Artificial Intelligence Research, vol. 67, no. 1, pp. 45–60, 2019.
51. T. Watanabe, Chil-Woo Lee, A. Tsukamoto and M. Yachida, “A method of real-time gesture recognition for interactive systems,” Proceedings of 13th International Conference on Pattern Recognition, Vienna, Austria, 1996.
52. T. Weng and X. Hu, “The Impact of Gesture-Based Interfaces on User Experience,” International Journal of Human-Computer Interaction, vol. 36, no. 15, pp. 1409–1421, 2020.
53. V. Kumar, S. Kumar, R. AlShboul, G. Aggarwal, O. Kaiwartya, A. M. Khasawneh, et al., "Grouping and sponsoring centric green coverage model for internet of things," Sensors, vol. 21, no. 12, p. 3948, 2021.
54. V. R. Vemula, "Adaptive threat detection in DevOps: Leveraging machine learning for real-time security monitoring," Int. Mach. Learn. J. Comput. Eng., vol. 5, no. 5, pp. 1–17, 2022.
55. V. R. Vemula, "Recent Advancements in Cloud Security Using Performance Technologies and Techniques," 2023 9th International Conference on Smart Structures and Systems (ICSSS), Chennai, India, pp. 1-7, 2023, doi: 10.1109/ICSSS58085.2023.10407744.
56. Y. F. Saputra and M. A. Al-Khasawneh, "Big data analytics: Schizophrenia prediction on Apache spark," in Advances in Cyber Security: Second International Conference, ACeS 2020, Penang, Malaysia, December 8-9, pp. 508-522, 2020.