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Original Article

Mobile Gesture Recognition for Accessibility: A Comparative Study of Machine Learning Algorithms

AnNing[1], Mazida Ahmad[2], Huda lbrahim[3]
[1,2,3]*Institute for Advanced and Smart Digital Opportunities (IASDO), School of Computing, Universiti Utara Malaysia, Sintok, Kedah, Malaysia.*

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Abstract: *This paper presents a comparative study of machine learning algorithms for mobile gesture recognition in the context of accessibility. The background of the study is the increasing importance of mobile devices and the need to make them accessible to individuals with different physical abilities. The purpose of this research is to evaluate different machine-learning algorithms and determine their effectiveness in recognizing gestures on mobile devices. The study employs a dataset of gesture samples collected from a diverse group of users. Various machine learning algorithms, including support vector machines, random forests, and neural networks, are implemented and compared based on their accuracy and computational efficiency. The results show that all three algorithms achieve high accuracy in gesture recognition, with support vector machines performing slightly better in terms of both accuracy and efficiency. In conclusion, this study provides valuable insights into the performance of different machine learning algorithms for mobile gesture recognition, contributing to the development of more accessible mobile interfaces.*

Keywords: *Mobile Gesture Recognition, Machine Learning Algorithms, Accessibility.*

I. INTRODUCTION

With the increasing prevalence of mobile devices and their importance in our daily lives, it is crucial to ensure that these devices are accessible to individuals with different physical abilities. Mobile gesture recognition technology plays a significant role in enhancing accessibility by allowing users to interact with their devices through a range of gestures. Machine learning algorithms have shown great potential in recognizing and interpreting these gestures accurately and efficiently.

This paper presents a comparative study of machine learning algorithms for mobile gesture recognition in the context of accessibility. This research aims to evaluate the effectiveness of different machine-learning algorithms in recognizing gestures on mobile devices. By comparing the performance of various algorithms, we can gain insight into their accuracy and efficiency in enhancing accessibility.

To conduct this study, we collect a dataset of gesture samples from a diverse group of users. The dataset comprises a wide range of gestures commonly performed on mobile devices. We then implement and compare three popular machine learning algorithms: support vector machines, random forests, and neural networks. These algorithms are widely used in gesture recognition tasks due to their proven effectiveness.

The evaluation of the algorithms is based on multiple performance metrics, including accuracy and computational efficiency. We aim to determine which algorithm achieves the highest accuracy in recognizing gestures while considering the computational resources required. The results of our study will provide valuable insights into the performance of different machine learning algorithms for mobile gesture recognition, contributing to the development of more accessible mobile interfaces.

In conclusion, this research contributes to the field of mobile gesture recognition for accessibility by providing a comparative study of machine learning algorithms. The findings of this study will aid developers and researchers in selecting the most effective algorithm for recognizing gestures on mobile devices. Ultimately, this research aims to improve the accessibility of mobile devices, ensuring that individuals with different physical abilities can fully utilize these technologies.

II. BACKGROUND AND LITERATURE REVIEW

A. Evolution of Mobile Gesture Recognition Technologies

In recent years, there has been a significant evolution in mobile gesture recognition technologies. These technologies have emerged as a result of the increasing popularity and widespread use of mobile devices, such as smartphones and

tablets. Mobile gestures refer to the hand movements and gestures made by users on the touchscreens of these devices to interact with various applications and functions.

Initially, mobile gesture recognition focused on simple gestures, such as swiping or tapping, which were used primarily for basic navigation purposes. However, with advancements in technology, the scope of gesture recognition has expanded to include more complex gestures, allowing users to perform a wide range of actions and tasks on their mobile devices.

This evolution has been driven by several factors. Firstly, mobile devices have become an integral part of our daily lives, used for communication, entertainment, shopping, and many other activities. As a result, there is a growing need to make these devices accessible to individuals with different physical abilities, such as those with disabilities or impairments.

Secondly, the rapid advancements in machine learning and artificial intelligence have paved the way for more sophisticated and accurate gesture recognition algorithms. These algorithms can analyze and interpret the patterns and motions in users' gestures, enabling mobile devices to understand and respond to these inputs effectively.

Furthermore, the availability of large datasets of gesture samples collected from diverse users has facilitated the development and evaluation of gesture recognition algorithms. These datasets allow researchers to train and test machine learning models, improving their accuracy and reliability.

In conclusion, mobile gesture recognition technologies have undergone significant evolution, driven by the increasing importance of mobile devices and the need for accessibility. This evolution has been supported by advancements in machine learning algorithms and the availability of large datasets. The study presented in this paper aims to contribute to this evolving field by evaluating different machine-learning algorithms for mobile gesture recognition.

B. Previous Studies and Findings on Gesture Recognition Algorithms

Several previous studies have focused on developing and evaluating gesture recognition algorithms for mobile devices. These studies have provided valuable insights into the performance and effectiveness of different machine learning algorithms in recognizing gestures.

In a study by Smith et al. (2017), a comparative evaluation of various machine learning algorithms, including support vector machines, random forests, and neural networks, was conducted to analyze their performance in gesture recognition. The results showed that support vector machines achieved the highest accuracy, followed by random forests, while neural networks had slightly lower accuracy.

Another study by Chen et al. (2018) explored the use of deep learning algorithms, specifically convolutional neural networks, for mobile gesture recognition. The study found that using deep learning algorithms improved the accuracy of gesture recognition compared to traditional machine learning algorithms. The authors concluded that deep learning algorithms have the potential to enhance the performance of gesture recognition systems on mobile devices.

Additionally, a study by Li et al. (2019) investigated the impact of different feature extraction techniques on the accuracy of gesture recognition algorithms. The study compared handcrafted features, such as histograms of oriented gradients, with learned features obtained from convolutional neural networks. The results demonstrated that learned features achieved higher accuracy in gesture recognition tasks, indicating the importance of feature extraction methods in improving the performance of machine learning algorithms.

Furthermore, Song et al. (2020) proposed a novel gesture recognition algorithm based on continuous hidden Markov models. The algorithm was specifically designed for real-time gesture recognition on mobile devices. The results showed that the proposed algorithm achieved high accuracy and computational efficiency.

Overall, these previous studies have contributed to the understanding of gesture recognition algorithms for mobile devices. They have highlighted the effectiveness of different machine learning techniques, such as support vector machines, random forests, neural networks, deep learning algorithms, and continuous hidden Markov models, in recognizing gestures. However, there is still a need for further research to develop more accurate and efficient algorithms, particularly in the context of accessibility for individuals with different physical abilities.

C. Contributions and Limitations of Earlier Research

Previous studies on gesture recognition algorithms have made significant contributions to the field of mobile accessibility. These studies have explored various machine learning algorithms and their effectiveness in recognizing gestures on mobile devices. The research has also highlighted the importance of making mobile devices accessible to individuals with different physical abilities.

One notable contribution of earlier research is the development and implementation of different machine learning algorithms for gesture recognition. These algorithms, such as support vector machines, random forests, and neural networks, have shown promising results in accurately recognizing gestures. The use of these algorithms has paved the way for improved accessibility of mobile devices.

Moreover, earlier research has shed light on the performance metrics used to evaluate the effectiveness of machine learning algorithms in gesture recognition. Accuracy and computational efficiency are two important metrics that have been extensively used in previous studies. These metrics provide valuable insights into the performance of different algorithms and allow for objective comparisons.

Despite these contributions, there are limitations to the earlier research on gesture recognition algorithms. One limitation is the lack of diversity in the datasets used for training and testing the algorithms. To ensure the accuracy and effectiveness of these algorithms for individuals with different physical abilities, it is crucial to include a diverse group of users in the dataset.

Another limitation is the focus on a limited number of machine learning algorithms. While support vector machines, random forests, and neural networks have been widely studied, there may be other algorithms that could potentially outperform these methods in terms of accuracy and efficiency.

In conclusion, earlier research on gesture recognition algorithms has made significant contributions to the field of mobile accessibility. These contributions include the development and implementation of various machine learning algorithms, as well as the use of performance metrics for evaluation. However, there are limitations to this research, such as the lack of diversity in datasets and the focus on a limited number of algorithms. This study aims to address these limitations and provide further insights into the performance of different machine-learning algorithms for mobile gesture recognition.

III. METHODOLOGY

A. Study Design and Data Collection

To conduct this comparative study of machine learning algorithms for mobile gesture recognition, a study design was developed and data collection was carried out. The study design aimed to ensure the collection of comprehensive and diverse gesture samples to evaluate the effectiveness of different algorithms.

A total of 100 participants were recruited for the study, with an equal distribution of individuals with different physical abilities, including individuals with no disabilities, individuals with motor disabilities, and individuals with visual impairments. This diverse group of participants was selected to ensure the representation of various gesture patterns and variations.

The participants were asked to perform a series of predefined gestures on mobile devices, including swiping, tapping, pinching, and rotating. The gestures were recorded using the device's built-in sensors, such as the accelerometer and gyroscope. Each participant performed each gesture multiple times to capture variability in gesture execution.

The data collection process was conducted in a controlled laboratory environment to minimize external factors that could potentially affect gesture recognition performance. Participants were provided with standardized instructions and given ample time to familiarize themselves with the gestures before recording.

The collected gesture samples were then pre-processed to extract relevant features, such as acceleration, orientation, and duration. These features were used as input to the machine learning algorithms for training and evaluation. The dataset obtained from the data collection process was divided into training and testing sets using a stratified random sampling approach. The training set, consisting of 70% of the data, was used to train the machine learning algorithms, while the remaining 30% served as the testing set for evaluating their performance.

In summary, the study design and data collection process ensured the representation of diverse gesture patterns and variations by recruiting participants with different physical abilities. The collected dataset provides a comprehensive basis for evaluating the performance of machine learning algorithms in mobile gesture recognition.

B. Description of Machine Learning Algorithms used in the study

In this study, three machine learning algorithms were implemented and compared for mobile gesture recognition. These algorithms include support vector machines (SVM), random forests, and neural networks. Support vector machines (SVM) are a popular algorithm for classification tasks. It works by finding an optimal hyperplane in a high-dimensional

space that maximally separates the different classes. SVM has been widely used in gesture recognition due to its ability to handle high-dimensional feature spaces and its effectiveness in handling complex data patterns.

Random forests are an ensemble learning method that combines multiple decision trees. Each decision tree is built using a random subset of features and a random subset of training samples. The final classification is determined by a majority vote of all the decision trees. Random forests are known for their robustness against overfitting and their ability to handle noisy data.

Neural networks are a class of machine learning algorithms inspired by the structure of the human brain. They consist of interconnected layers of artificial neurons, with each neuron performing a weighted sum of its inputs followed by a non-linear activation function. Neural networks can learn complex patterns and are widely used for various classification tasks.

For the implementation of these algorithms, we utilized open-source libraries and frameworks such as sci-kit-learn and Tensor Flow. The dataset used in this study consisted of gesture samples collected from a diverse group of users. We trained and evaluated each algorithm using a cross-validation approach to ensure reliable performance assessment. The performance of each algorithm was measured in terms of accuracy and computational efficiency. The accuracy represents the percentage of correctly recognized gestures, while the computational efficiency measures the time required for training and inference.

The results of our study showed that all three algorithms achieved high accuracy in gesture recognition. However, support vector machines (SVM) performed slightly better in terms of both accuracy and efficiency compared to random forests and neural networks.

In conclusion, the implementation and comparison of these machine learning algorithms provided valuable insights into their effectiveness in mobile gesture recognition. The findings contribute to the development of more accessible mobile interfaces for individuals with different physical abilities.

IV. RESULTS AND DISCUSSION

A. Comparative Evaluation of Machine Learning Algorithms Based on Performance Metrics

To evaluate the effectiveness of different machine learning algorithms for mobile gesture recognition, a comparative analysis was conducted using various performance metrics. The algorithms examined in this study include support vector machines (SVM), random forests (RF), and neural networks (NN).

The evaluation was based on two main performance metrics: accuracy and computational efficiency. Accuracy measures the percentage of correctly classified gestures, while computational efficiency considers the time required to train and tests the algorithms. The dataset used for the evaluation consisted of gesture samples collected from a diverse group of users, ensuring a representative sample. The dataset was divided into training and testing sets to assess the algorithms' performance.

For each algorithm, multiple iterations were executed to capture the variations in performance. The average accuracy and computational efficiency were calculated to provide a more reliable evaluation. The results of the comparative analysis showed that all three machine learning algorithms achieved high accuracy in gesture recognition. However, support vector machines demonstrated slightly higher accuracy compared to random forests and neural networks.

In terms of computational efficiency, support vector machines also outperformed random forests and neural networks. The training and testing time required by the support vector machines algorithm was relatively shorter compared to the other two algorithms.

These findings suggest that support vector machines may be the most suitable algorithm for mobile gesture recognition in terms of both accuracy and efficiency. However, it is important to note that the performance of the algorithms may vary depending on the specific dataset and implementation parameters.

Overall, this comparative study provides valuable insights into the performance of different machine learning algorithms for mobile gesture recognition. The results contribute to the development of more accessible mobile interfaces and can guide future research in this field.

B. Insights and Implications from the Study Findings

The comparative evaluation of machine learning algorithms for mobile gesture recognition yielded several key insights and implications. Firstly, all three algorithms - support vector machines, random forests, and neural networks -

achieved high accuracy in gesture recognition. This indicates that machine learning techniques are effective for recognizing gestures on mobile devices in the context of accessibility.

Secondly, support vector machines demonstrated slightly better performance in terms of both accuracy and computational efficiency compared to the other two algorithms. This suggests that support vector machines may be a preferred choice for implementing gesture recognition systems on mobile devices, as they can achieve accurate results while minimizing computational resource requirements.

The findings also highlight the importance of using a diverse dataset for training and testing the machine learning algorithms. By collecting gesture samples from a diverse group of users, the study ensured that the algorithms were trained to recognize gestures performed by individuals with different physical abilities. This enhances the inclusivity and accessibility of mobile interfaces by catering to the needs of a wider user base.

Furthermore, the comparative evaluation of the algorithms provides insights into their strengths and weaknesses. For instance, random forests have the advantage of being able to handle large datasets and high-dimensional feature spaces, but they may be prone to overfitting. On the other hand, neural networks have the potential for more sophisticated pattern recognition, but they require larger amounts of training data and computationally intensive training processes. These insights can guide future research and the development of more optimized machine-learning algorithms for mobile gesture recognition.

Overall, this study contributes to the field of accessibility by providing valuable insights into the performance of different machine-learning algorithms for mobile gesture recognition. The findings can inform the development of more accessible mobile interfaces, ensuring that individuals with different physical abilities can effectively interact with mobile devices. Furthermore, the study emphasizes the importance of considering a diverse user group in the design and evaluation of gesture recognition systems to ensure inclusivity and accessibility. Further research could explore the integration of multiple machine learning algorithms or the combination of machine learning with other techniques to enhance the accuracy and efficiency of mobile gesture recognition systems.

V. CONCLUSION

The comparative study of machine learning algorithms for mobile gesture recognition in the context of accessibility has provided valuable insights into their performance. The study employed a diverse dataset of gesture samples collected from users with different physical abilities. Three machine learning algorithms namely support vector machines, random forests, and neural networks, were implemented and compared based on accuracy and computational efficiency metrics. The results revealed that all three algorithms achieved high accuracy in gesture recognition, with support vector machines slightly outperforming the others in terms of both accuracy and efficiency.

These findings contribute to the development of more accessible mobile interfaces, as they provide evidence of the effectiveness of machine learning algorithms in recognizing gestures on mobile devices. By understanding which algorithms perform better, developers can make informed decisions when designing gesture recognition systems for individuals with different physical abilities. The study also highlights the importance of considering accessibility in the design and development of mobile devices, as they play an increasingly important role in our daily lives.

However, it is important to note the limitations of this research. The study focused solely on comparing machine learning algorithms and did not explore other factors that could impact gesture recognition, such as sensor placement or user interaction techniques. Future research should consider these factors to further enhance the accessibility of mobile interfaces. Additionally, while the dataset used in this study was diverse, it may not fully represent the entire population. Further studies with larger and more diverse datasets are needed to validate the effectiveness of the identified algorithms.

In conclusion, this comparative study provides evidence of the effectiveness of machine learning algorithms, particularly support vector machines, in mobile gesture recognition for accessibility. It contributes to the field by highlighting the importance of considering accessibility in the design and development of mobile devices. The findings of this research can guide the development of more accessible mobile interfaces, ultimately improving the user experience for individuals with different physical abilities.

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