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# An Investigational Study on Hand Gesture Recognition By Accelerometer-Supported Systems

Ms. Rajeswari.s,
*Master Of Engineering,*
*Department of Computer Science and Engineering,*
*Engineering KIT-KalaignarKarunanidhi Institute Of Technology*
*Of Technology( Affiliated to Anna University),*
*Coimbatore,India .*

Ms.Jayanthi.M
*Assistant Professor ,*
*Department of Computer Science and*
*KIT-KalaignarKarunanidhi Institute*
*( Affiliated to Anna University)*
*Coimbatore,India.*

***Abstract -*** *In the current research scenario, human activity recognition seems to be important in people's daily lives because of its capacity to acquire comprehensive high-level information about human activity from wearable or fixed equipment. The scientific community in the current era has used a variety of methodologies like machine learning, deep learning, Internet of Things (IoT), big data analytics, etc., to categorize human activities. Even though, hand gestures recognition-based research designs are under progress for various application domains. In this study, the current efforts based on a wide variety of hand gesture recognition models are highlighted. This research study focuses on accelerometer-supported data acquisition technologies, which are widely used in human activity recognition. This research study evaluates the top 15 existing models proposed by various researchers from 2021-2022. Thus, summarizes their work in terms of the strengths and weaknesses of each work and finallysuggests the best algorithmic models for hand gesture recognition.*

***Keywords:*** *Human Activity Recognition, Hand Gesture, Accelerometer, Machine Intelligence, Fuzzy-Neural Network*

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## I. INTRODUCTION

Due to the widespread usage of user scenarios, the tremendous growth of sophisticated algorithms, and the development of innovative sensing techniques, human activity recognition has become a focus of intense study during the past 10 years [1]. Ambient-assisted living, nursing homes, health monitoring, rehabilitative activities, surveillance, and human-computer interaction are among the most effective uses of human activity recognition. Identifying the physical acts carried out by a particular individual or group of persons is the aim of human activity recognition, depending on the application [2-4]. Some of the actions, such as running, leaping, walking, and sitting, can be carried out by a single person due to modifications in the complete body. Some actions, such as hand gestures, and eye gazing, are carried outusing a specific body component movement [5-8].

Since some studies either offered a vast array of sensing and data processing techniques or a narrow subset of the field, such as wearable sensing and video-based sensing, many human activity recognition-related sensing surveys had a weak focus on sensing techniques [9–12]. Many researchers make an effort to present a complete, in-depth review of the state-of- the-art sensing modalities in human activity recognition tasks in order to provide younger researchers in the area with a thorough understanding of the many sensing concepts. This study focuses on hand gesture recognition models among other different human activity recognition models in recent trends. Despite the effectiveness of vision-based recognition algorithms, hand gesture recognition by extraction from video sequences acquired by cameras has become popular [13]. However, there are many possibilities for information privacy exposure due to visual-based recognition devices' vulnerabilities that continually record users' lives, which raises security risks [14]. Additionally, real-time applications might provide significant processing challenges when attempting to extract gesture information from video sequences.

Hand gesture recognition models based on the sensory input generated by sensors other than cameras are alternatives to visual-based hand gesture recognition [15]. Even if a sensor-based recognition method's computing cost might be decreased, it is often difficult to extract gestures from sensory input for classification models. Even a perfect gesture extraction from sensory data might be difficult in some cases because gesture motions could not be simply inferred from the appropriate sensor values [16–17]. It is feasible to consider the detection of objects as a problem when recognizing gestures from sensory input. A difficult and crucial issue for computer vision applications is object recognition from images [18]. However, examples of widely used sensors include accelerometers, gyroscopes, photoplethysmography, flex sensors, electromyography (EMG), and a combination of these sensors. Accelerometers among these sensors can be effectively used in object detection and hand gesture recognition models with minimal effort and it ensures better performance [19-20].

### *A. HANDGESTURE RECOGNITION USING ACCELEROMETERS*

Machines can read hand gestures statistically using a technique called hand gesture recognition. It can be applied to make human-computer interaction easier. For applications including controlling gadgets, entertainment, healthcare, and education, gesture recognition is successful [21]. Figure 1 shows the general architectural model of hand gesture recognition using accelerometers and gyroscopes. The given explains the basic flow of hand gesture recognition where the accelerometer attached to hardware like gloves, smart watches, etc collects the movement signals of the hand. This raw data is then passed to the next stage of data preprocessing which preprocesses the signals by removing the noise, eliminating the drifts, transforming the coordinates, filtering, etc.

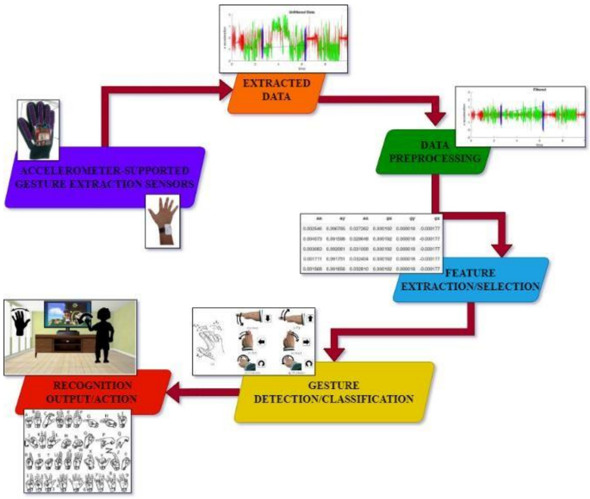


**Figure 1: General architectural model of hand gesturerecognition using accelerometers**

The preprocessed signals are then transferred to the feature engineering stage if the hand recognition system implements machine learning algorithms or is directly given to the trained deep neural network where the feature engineering is performed by the deep neural network implicitly [22]. Feature engineering involves feature extraction and selection, the extracted features are then used to train the classification or detection model using machine intelligence.

The three-axis linear acceleration has been computed by merging the detected hand movement data with complementary filters in the hand gesture recognition models employing accelerometers and gyroscopes [23-24]. The axis- crossing code by logging the order in which acceleration vectors crossed axes in the world coordinate frame can be implemented in processing the hand gesture data collected from the accelerometer and gyroscopes. Many of the research works deployed hand gesture recognition techniques in sign language detection and classification, remote control, medical assistance, etc [25-27]. Some real-time solutions using hand gesture recognition models with accelerometers use the recognized outputs to trigger the physical or simulation activities. This research survey studies 15 different hand gesture recognition models using accelerometers proposed from 2021 to 2022. The methodologies proposed by each work along with strengths and weaknesses are summarized and evaluated to give the significance and scope of hand gesture recognition using accelerometers. The following sections discuss the existing works on hand gesture recognition using accelerometers, followed by the observational results. After this, this article presents a novel hand gesture recognition model using a fuzzy neural network. Finally ends up with a conclusion and a bibliography.

## II. EXISTING WORKS

This section summarizes the existing works done by different authors on hand gesture recognition using accelerometers. This section categorizes the existing works based on the data processing technologies like machine learning and deep learning.

### *A. USING MACHINE LEARNING ALGORITHMS*

Numerous research on human activity recognition including hand gesture recognition systems, eye gaze movement detection systems, etc., used machine learning algorithms and deep learning algorithms. However, this section covers machine learning algorithm-based hand gesture recognition systems.

Ahamed et al., (2021) proposed a strategy to transform hand gestures into an annotated explanation [28]. They modeled the Malaysian Sign Language (MSL) recognition framework which used an accelerometer-supported DataGlove to capture the hand gestures. Based on information gathered by DataGlove, the framework was composed of three sub- modules for the detection of static isolated signs. The criteria for a sign recognition system were determined by the first module's focus on the features of signs. The different processes necessary to create a wearable sign-capture device were described in the second module. The real-time sign language detection method using a pattern algorithm based on a support vector machine (SVM), was covered in the third module.

Using a hyperdimensional computational model [29] to simulate dual-stage classification in a memory-efficient way, authors Zhou et al. (2021) have reported sensor fusion of accelerometer and EMG inputs. They presented two techniques for storing accelerometer data that might be utilized as a key to finding position-specific features among a group of stacked models. They were able to improve the classification accuracy from a model trained exclusively on EMG and accelerometer to up to 93.34% by evaluating the model on a dataset including 13 gestures in 8 limb postures. By using 8 less memory than a standard dual-stage classification architecture and only slightly more memory than a single limb position model, they were able to achieve their goal.

Using machine learning models including artificial neural network (ANN), decision tree (DT), random forest (RF), and KNN. Siddiqui et al. (2021) proposed a hand gesture identification model with a tri-axial accelerometer and gyroscope support that can recognize autistic gestures [30]. The information was transmitted to a server for data collection and categorization through a Bluetooth link. Ten autistic kids were used, and they were asked to repeat each gesture about ten times to create a dataset of 24 movements. The time- and frequency-domain properties from the sensor data were extracted, and the data was then categorized using ML models,with an average accuracy of 91%.

Mahzabin et al. (2021) chose to use two distinct datasets, American Sign Language (ASL), and a generic hand gesture dataset [31] to detect unique static and dynamic gestures for the universal English language using the three different machine learning models, including ANN, KNN, and decision tree. All of the classifiers used had good accuracy on both datasets, and the results were much better after normalization. It was proposed to modify the different layers to create the ANN model with a 99.40% accuracy, the KNN model attained an accuracy of 99.14%, and the DT model's accuracy of 94.52%.

The parameters for creating an SVM model for hand gesture detection in intelligent lighting control were assessed by Ameliasari et al., (2021) [32]. In this investigation, eight predetermined motions were used to turn on and off four different lights. Data were then gathered using a wristwatch equipped with an accelerometer and inertial measurement unit (IMU) sensor. The 36 features collected from each gesture data set are then selected using Pearson Correlation. To assess the impact of gesture selection on model performance, two sets of gestures were examined. According to the authors, a different set of gesture selections is needed for a model to function well when implementing gesture detection using SVM.

A DataGlove with 5 flex sensors, a 3-axis gyroscope, and a 3-axis accelerometer (ACC) was employed by Faisal et al. (2021) to classify both static and dynamic hand gestures in real-time [33]. The data were collected from 35 individuals who used DataGlove to make 14 static and 3 dynamic movements. Then accurately determined an orientation and motion profile using mathematical algorithms on the accelerometer and gyroscope data, and they preprocessed the raw flex sensor data using digital filtering methods. Four classic ML methods, including KNN, DT, SVM, and RF, were applied to both datasets and assessed. They were able to achieve maximum accuracy of 99.53% for static gestures and 98.64% for dynamic motions using the KNN classifier. They provided wireless real-time hand gesture detection for recognizing human-computer interaction and sign language.

Amin and Rizvi (2022) emphasized the smart prototype that incorporated flex, accelerometer, and gyroscope sensors to record sign gestures [34]. These sensors were attached to a glove to collect and create datasets of alphanumeric data, such as 0–10 and A–Z, and digits, such as 0–10. Their approach identified the true meaning of performed gestures by deaf- mute people and categorized sign movements. SVM, KNN, and discriminant analysis were trained on manually created datasets, and they achieved average accuracy rates of 99.82%, 99.18%, and 99.03%, respectively.

Roberge et al. (2022), suggested an algorithmic method for recognizing hand gestures that were intended to serve as the central element of the improved fine-grained activity recognition model [35]. The authors performed an analysis based on inertial data obtained from the uniquely designed wristband fitted with a gyroscope, and triaxial accelerometer and assessed using ML methods including Classification and Regression Trees (CART), KNN, RF, Nave Bayes (NB), SVM, DT, and multi-layer perceptron (MLP). To characterize extensive cooking activities, a straightforward collection of gestures has been established. To do this, they created access to the scientific community-tagged dataset of participant- performed atomic movements. They were able to recognize the gestures with an average accuracy of 0.83 by taking out one participant from the analysis.

### *B. USING DEEP LEARNING ALGORITHMS*

This subsection summarizes the deep learning-based hand gesture recognitions. Among many such recognition models, the most recent and significant proposals are discussed here.

Mali et al. (2021) provided an end-to-end hand gesture recognition system that leverages a three-axis accelerometer data stream from Microelectromechanical systems (MEMS) to identify gestures in real-time [36]. Deep learning and transfer learning models were used in this system. To remotely convey gestures to personal computers and operate them, via Bluetooth was employed. Users can contribute their gestures to a library of pre-existing gestures to build a system that would be entirely configurable. Action Mapping Interface, a multipurpose desktop application, was installed to test the system. It reproduced mouse and keyboard actions and carried out intricate commands using deep learning gestures (DNN). A unique method of hand gesture detection employing smartphone sensor reading was offered by the researchers Sachdeva and Mohan (2021) and could be used to interface with personal computers [37]. The approach described the model that gathers data from smartphone sensors (accelerometer and gyroscope), and, based on the sensor data classifies the data using a deep neural network.Additionally, the gesture was mapped to action once it hadbeen correctly identified.

They created a software application that detects and categorizes a wide range of arm and hand movements. According to the author, these qualities can be utilized by the implementations to fulfill changing demandsfor realistic and practical human-computer interaction.

For the purpose of recognizing hand motions, Tong et al. (2022) put forth the Bidirectional-Gated Recurrent Unit- Inception (Bi-GRU-I) deep learning model [38]. The dataset known as Command Actions of Traffic Police is used in conjunction with inertial sensors, such as an accelerometer, to capture triaxial acceleration signals during hand motions (CATP). The three datasets used in comparison studies with the accelerometers obtained dataset were the self-collected CATP dataset, the widely used Wireless Sensor Data Mining (WISDM), and the University of California, Irvine (UCI- HAR) dataset. Higher performance and greater robustness were shown in the proposed model by the researchers. In addition, the optimization of the sensor arrangement was examined, and it was demonstrated that this approach could be used for tasks requiring fewer sensor units.

In this current research scenario, there is currently ongoing research on pen interfaces and recognition techniques. Lopez-Rodriguez et al. (2022) recommended Convolutional Neural Networks (CNN) and Long Short-Term Memory for usage in a handwritten character recognition system based on 3D accelerometer data processing (LSTM) [39]. While wearing a MYO armband on the forearm, the user initially created a multi-stroke freestyle character on a touchpad using their finger or a pen. The 3D accelerometer signals generated during writing were then identified using a CNN, LSTM, or CNN-LSTM network. The spatial parameters produced by the convolutional backbone were input into an LSTM that extracts short-term temporal information. When put to the test against a proprietary dataset of 3D accelerometer data collected from several users utilizing an armband device, the system's accuracy rose by 53%.

Lin et al. (2022) suggested a hand gesture recognition system and a device using just light-emitting diode (LED) panels [40]. This system includes six LED screen modules and a conventional FPGA (field-programmable gate array) to operate the display and collect data for the deep learning model. The LED detects informational light changes without interfering with display functionality, therefore indicating a variety of movements. The recognition approach was implemented using static bidirectional long short-term memory (S-Bi-LSTM), which relies on both time- and frequency- domain features of gestures. The results of trials using the various hand gestures of different persons in a setting with complex backdrop lighting showed that gesture identification accuracy may reach up to 93.60%. With the method of frame segmentation for dynamic gesture activities, a better dynamic Bi-LSTM (D-Bi-LSTM) algorithm was also recommended. To increase the accuracy of dynamic gesture detection up to 91.67%, this approach separates dynamic gestures into three components and feeds each portion into a different classifier.

Robotic machine development has the potential to advance construction automation. A method for identifying hand gestures for construction workers integrated with robotics using wearable sensors on fingers was proposed by Wang et al., (2022) [41]. Synchronizing, standardizing, and smoothing finger movements were the first steps of the system. An improved fully convolutional neural network (FCN) was therefore the hand gestures data acquired from the accelerometers through a sliding. In a system validation test, the system passed with an accuracy of 85.7% and a recall of 93.8%, respectively. The suggested method was recommended to use for enabling communication with a robotic dump truck in a test project.

The transformer model, which was integrated with a deep learning-based neural network model, was developed by Luptáková et al. (2022) primarily for applications in vision and natural language processing [42].

For a time-series analysis of hand gesture signals, it was revised and improved the significant results. The performance of the transformer's self- attention mechanism, which highlights specific correlations between signal levels within a time series, was incomparable to that of modern CNN-LSTM. On the largest publicly accessible dataset of smartphone motion sensor data spanning a variety of activities, the performance of the suggested personalized transformer approach was assessed, and their results showed that it achieved an average identification accuracy of 99.2% as opposed to 89.67% acquired on the same data by a traditional machine learning method.

## III. OBSERVATIONAL ANALYSIS

The observational evaluation section presents the summarized analysis of the literature survey done in terms of technology used, strengths, and weaknesses. The signal qualities of gestures, especially hand gestures, include two elements that make it challenging to recognize them. They start out by presenting segmentation ambiguity. Second, even for the same motions and the same individuals, they exhibit temporal and spatial diversity. Different hand gesture recognition systems often use models that use machine learning, deep learning, transfer learning, etc. to try to mimic the brain's problem-solving process. The neural network can build a system that makes judgments and performs classifications by using previously solved issues, similar to how individuals use information learned through experience to new problems or circumstances. Neural network-based solutions are appropriate for issues where there is no precise computational answer or where the implementation of the solution would need exceedingly complex methods.

***Table 1: OBSERVATIONAL RESULTS***

| REFERENCES | TECHNIQUE USED | APPLICATION | STRENGTHS | WEAKNESSES |
|---|---|---|---|---|
| | | *Hand Gesture Recognition Using Machine Learning Algorithms* | | |
| **In [28]** | Pattern Matching Algorithm based on SVM. | Malaysian Sign Language | i) Presents DataGlove for ambiguous gesture recognition related to hand position issues.<br>ii) Provide both software and hardware prototyping. | i) It has not yet been considered how to position the hands in relation to the body of the signer.<br>ii) Computational efficiency is not evaluated properly.<br>iii) Model specific to static gestures |
| **In [29]** | KNN and SVM with orthogonal context encoding. | Limb position and hand gesture classification for health monitoring. | i) Improved classification accuracy of 98.4%.<br>ii) Unique proposal for data processing (data encoding) other than classification<br>iii) Multi-context biosignal classification applications can be applied to the proposed model. | i) Signal distortion was not evaluated and needs to improve the classification performance. |
| **In [30]** | KNN, DT, ANN, and RF | i) Gesture Recognition of Autism Spectrum Disorder Children.<br>ii) Comparative analysis of classification algorithms on real-time experiment with 10 autistic children | i) Showed the significance of ML algorithms in hand gesture recognition with average accuracy of 91%.<br>ii) Provide both software and hardware prototyping. | i) Lower classification accuracy compared to other research results. |
| **In [31]** | ANN, KNN, and DT | i) American Sign Language (ASL) and a general gestures classification.<br>ii) Comparative analysis of classification algorithms on sign language detection and gesture recognition | i) Significant classification performance with accuracy of 99.40% (ANN), 99.14% (KNN), and 94.52% (DT).<br>ii) Best for both static and dynamic gestures. | i) Computational complexity was not specified. |

| | | | | |
|---|---|---|---|---|
| **In [32]** | KNN, DT, SVM, and RF with pearson correlation-based feature selection | Internet of Things (IoT) environment for smart lighting control | i) Perform both gesture selection and feature selection for lighting control.<br>ii) Greatest scope for real-time deployment and commercialization.<br>iii) Provide both software and hardware prototyping. | i) Performance of the system depends on the choice of gestures.<br>ii) Largest size of the data dimension lowers the performance accuracy. |
| **In [33]** | KNN with digital filtering techniques | i) Sign Language Recognition (SLR) and real-time Human-Computer Interaction (HCI)<br>ii) Comparative analysis of classification algorithms | i) Best for both static and dynamic gestures.<br>ii) Performing accurate orientation and motion profile. | i) Need support of gyroscope, and flex sensors other than accelerometer for best results.<br>ii) Cost ineffective |
| **In [34]** | KNN, discriminant analysis, and SVM | i) American sign language recognition<br>ii) Alphanumeric gesture classification<br>iii) Alphabet gesture classification | i) Provide both software and hardware prototyping.<br>ii) Given better classification accuracy of 99.18%, 99.03%, and 99.82% for KNN, discriminant analysis, and SVM, respectively. | i) Need support of gyroscope, and flex sensors other than accelerometer for best results.<br>ii) Specific to static gesture recognition |
| **In [35]** | CART, KNN, RF, NB, SVM, DT, and MLP | i) Complete fine-grained cooking activities recognition model smart homes.<br>ii) Comparative analysis of classification algorithms on sign language detection and gesture recognition | i) Provide both software and hardware prototyping.<br>ii) Greatest scope for real-time deployment and commercialization. | i) Lower classification accuracy (average accuracy of 83%) compared to other research results. |
| ***Hand Gesture Recognition Using Deep Learning Algorithms*** | | | | |
| **In [36]** | DNN with Microelectromechanical systems(MEMS) | Customized system with an Action Mapping Interface on mouse & keyboard control | i) Highest performance evaluation with an accuracy of 97.71%<br>ii) Can support realt-me gesture recognition remotely via Bluetooth technology | i) Signal distortion has to be measured since it involves real-time communication.<br>ii) Long range communication was not handled. |
| **In [37]** | Deep-CNN | Action Mapping Interface on keyboard control for an active gameplay environment. | i) Better performance on accuracy with 99% compared to machine learning algorithms.<br>ii) Better computational efficiency with minimal processing time. | i) Limited to mobile application development. |
| **In[38]** | Bi-GRU-I | Command Actions of Traffic Police (CATP) | i) Improved performance accuracy with 96.11%.<br>ii) Simulated three different dataset<br>iii) Proposed combined deep learning model with unique feature extraction | i) No real-time data acquisition<br>ii) Low processing speed<br>iii) Failed to handle complex transition activities. |
| **In [39]** | CNN-LSTM, CNN, and LSTM | i) Handwritten English character recognition<br>ii) Comparative analysis of classification algorithms on sign language detection | i) Recognize Multi-stroke freestyle characters like English letters and digits.<br>ii) Evaluated computational efficiency. | i) Lower computational speed for CNN-LSTM due to a longer training period.<br>ii) Limited experimental analysis with test to isolated letters and digits.<br>iii) Myo armband usage is not as widespread as Android device usage.<br>iv) For capturing handwritten characters, it depends only on a tablet or touchpad. |

| | | | | |
|---|---|---|---|---|
| **In [40]** | S-Bi-LSTM and D-Bi-LSTM | HCI system with LED sensing ability | i) Provide both software and hardware prototyping.<br>ii) Best for both static (S-Bi-LSTM) and dynamic (D-Bi-LSTM) gestures.<br>iii) Given better performance even in complex background illumination.<br>iv) Cost-effective solution<br>v) It can be promoted easily and is contactless and safe. | i) Demand improved communication speed since it is meant for real-time deployment. |
| **In [41]** | FCN | Human-Robot Collaboration for construction workers using a robotic dump truck | i) Unique application domain selection<br>ii) Significant performance in terms of recall and precision | i) Higher computational cost<br>ii) Need high-end robotic engineering for real-time implementation |
| **In [42]** | CNN-LSTM | Health Monitoring | i) Effective feature extraction. | i) Not specific to hand gesture recognition |
| | | | ii) Best suited for table tennis practice and assistance | ii) Recognition accuracy can be improved in the future. |

The above table summarizes the evaluation results of this literature survey. It is very clear that much of the research performs hand gesture recognition on sign language recognition. While comparing the different research models using machine learning, it is observed that among many ML algorithms, the best performance results observed for hand gesture recognition were given by KNN and SVM models. Whereas, while comparing the performance of hand gesture recognition systems using deep learning algorithms, CNN and LSTM had given the best performance results.

## IV. CONCLUSION

The comprehensive literature research is summarized in this study report. This study finds that the scope of machine learning algorithms like KNN and SVM in hand gesture recognition is significant. Similarly, deep learning algorithms such as LSTM, CNN, and even combined CNN-LSTM models can support hand gesture recognition with better performance. Furthermore, this research survey finds the research gap of fuzzy-based neural networks in hand gesture recognition models and planned to extend this research by developing a novel hand gesture recognition model using accelerometers using the same.

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