

REPUBLIC OF TURKEY

FIRAT UNIVERSITY

GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCE



**Gesture Learner Machine for Recognizing
Symbols and Numbers
Chia Fatah Aziz**

Master Thesis

Department: Software Engineering

Supervisor: Prof. Dr. Asaf VAROL

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MASTER THESIS

CHIA FATAH AZIZ

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Thesis Supervisor: Prof. Dr. Asaf VAROL (F.Ü.)

Other Juries: Assoc. Prof. Dr. Fatih ÖZKAYNAK (F.Ü.)

: Assoc. Prof. Dr. Özal YILDIRIM (M.Ü.)

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DEDICATION

This thesis is dedicated to my wonderful family for their love and measureless support, and it is also dedicated to all of my friends who have supported me to get my Master degree.

CHIA FATAH AZIZ

Elazığ, 2017

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ÖZET

Sembolleri ve Sayıları Tanıma için Hareket Öğrenen Makine

El hareketi tanıma (Hand Gesture Recognition-HGR) son yıllarda daha büyük ve güçlü bir şekilde dikkat kazanan bir sistemdir. Bunun nedeni, kullanışlı uygulamaları ve insan bilgisayar etkileşimi (Human Computer Interaction-HCI) kavramına dayanarak makine ile etkin bir şekilde iletişime geçebilmesidir. Bu tez, bir yazılım aracı kullanarak HGR sistemi için bir yaklaşım sunmaktadır. Geliştirilen sistem, gerçek zamanlı görüntüyü bir girdi olarak okur ve bunu el işaretlerinin eğitim seti örnekleriyle karşılaştırır. Bu yaklaşımda, eşik bölgelerinin tespiti için deri algılama tekniği kullanılmıştır ve kullanılan el hareketleri ve tanıma işlemi için k-En Yakın Komşu (k-NN), Naive Bayes (NB) ve Destek Vektör Makinesi (SVM) olmak üzere üç makine öğrenmesi metodu kullanılmıştır. Kullanılan el hareketleri Irak işaret dilinde kullanılan sayı ve sembolleri tanımak için derinlik algılayıcısı olan bir Kinect kamera kullanarak alınmıştır. Bu tezde sunulan sonuçlar, özel ihtiyaçları olan bireylerle normal bireyler arasındaki iletişimin iyileştirilmesinde gerçekleştirilmiştir. Buna ek olarak, sunulan çalışma farklı ülkelerdeki işaret dillerinin manasını anlamak için araç olarak kullanılabilir.

Anahtar Kelimeler: El Hareketleri, İnsan Bilgisayar Etkileşimi, Kinect, K-En Yakın Komşu, Naive Bayes, İşaret Dili, Destek Vektör Makineleri

ABSTRACT

Hand Gesture Recognition (HGR) is a system that has gained a great and more powerful attention in the recent years. This is due to its useful applications and the ability to contact with machine effectively based on the concept of Human Computer Interaction (HCI). This thesis presents an approach for HGR system using a software tool. The developed system reads the real time image as an input and then it compares it with the training set samples of hand signs. In this approach, for detecting the threshold regions, skin detection technique has been used and for recognition process three Machine Learning methods have been used such as k-Nearest Neighbors (k-NN), Naïve Bayes (NB) and Support Vector Machine (SVM). The used hand gestures are for recognizing numbers and symbols available in the Iraqi sign language using a Kinect camera that has a depth sensor. The results presented in this thesis are realized in improving the communication between individuals with special needs and normal individuals. In addition, the presented work can be used as means for understanding the meaning of sign language in different countries.

Keywords: Hand Gesture, Human Computer Interaction, Kinect, k-Nearest Neighbor, Naïve Bayes, Sign Language, Support Vector Machine

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1.INTRODUCTION

Biometric is a process of assessment and factual inspection of people's behavior and physical characteristics. Biometrics are used for identification authentication and access control which shows that everyone is unique and can be identified by certain physical and behavioral characteristics. The gesture is a mechanism used for the communication between machine and human. For a convenient human interaction, this mechanism requires an interface for Hand Gesture Recognition (HGR) system.

In Human Computer Interaction (HCI) and computer vision fields, hand gesture recognition is very important; and with the objective of bringing the performance of human-human interaction close to HCI, it has become an active area of research. HGR has a diverse area of applications in reality, such as the communication in video conferencing [1], using a finger as a pointer for selecting options from a menu, and Sign-language Recognition (SLR) [2, 3].

HGR is one of the most significant research topics in the field of HCI, due to its expansive applications in computer games, virtual reality, and sign language identification. Despite the availability of previous research attempts, building a robust HGR system, that is applicable for real life applications, remains a challenging problem. Existing vision-based approaches are greatly limited by the quality of the input image from optical cameras [4, 5]. Consequently, these systems have not been able to provide satisfactory results for HGR. HGR systems face two main challenging problems, namely hand detection, and gesture recognition. The implementation of hand gesture involves consequential usability challenges, including high recognition accuracy, fast response time, learning speed, and user satisfaction. This helps explaining why only some vision-based gesture systems have matured beyond prototyping or managed to get into the commercial marketplace for human computer devices [6, 7].

Kinect is a very well-defined motion sensing input device developed by Microsoft for the Xbox 360 video game console and Windows PCs. The product is specialized by having a depth sensor, an RGB camera and a multi-array microphone running on a proprietary software. It supplies a full-body 3D motion capture, voice recognition, and facial recognition abilities. Under any ambient light condition, the depth sensor captures the video data in 3D. Microsoft

Kinect produces a cheap, simple and perfect method for real-time individual interaction with computer applications [8].

Throughout the life associated with humans, it is always cumbersome for some people who are unable to speak or deaf people, to create a proper communication. This communication may be between individuals unable to speak, or those who speak normally for other reasons. Therefore, there should be a sort of interpretation between the parties to translate the speaker's word or phrase to the deaf or mute individuals and vice-versa. Thus, it is convenient and useful to produce a learning concept through which deaf and ordinary individuals may communicate. This can be achieved by producing a mutual vision for the meaning of all words by signs as well as the hand gestures, allowing a common understanding without any middle translation. An individual can move a hand in front of a webcam to control the meaning of his/her sign or gesture, which will provide those who are deaf or dumb a means for communication with ordinary people [8].

2. LITERATURE REVIEW

Machine Learning (ML) and Artificial Intelligence (AI) are considered a branch of computer science and engineering that focuses on many applications. AI is an area of study concerned with conveying an intelligent human behavior to computer devices. The aim of this Hand Gesture Recognition (HGR) research work is to develop a Window-based application that provides an intelligent contact solution to public and private sectors. Here, Hand Gesture Recognition System (HGRS) is a system that can be used to save images of hands in a database, after that the system can be used for detecting and recognizing hand gestures in order to convey the full meaning of all hand signs.

Human Computer Interaction (HCI), also called Man-Machine Interaction (MMI), makes a reference to the contact between the machines, exactly the computer, and the human; or between people to understand each other, since the computer is unimpressive without appropriate utilize by the user or human [9].

The fundamental aim of creating or making a system for HGR is to make a natural association between human and machine or computer. This system is essential especially when the recognized gesture and symbols can be more important and have a useful way of conveying the meanings of full information for Arabic Sign Language (ArSL) between human and machine, which can also be used for robot control [10].

There are two types of gesture, static hand gesture which is considered less computationally complex and the dynamic hand gesture which is a sequence of posters and computationally more complex compared to its static counterpart. However, it is great and suitable for a real-time environment [10, 11]. There are some methods for recognizing hand gestures, some of which need hardware devising and implementation, for example, data glove devices and color marker, to easily extract extensive characterization of features of gesture. While some other methods are based on the presence of the hand by using the color of skin to segment the hand and extract the required features [12].

There are many applications that make hand gesture important in our life, such as, games, HCI, robotics and many more which usually use different algorithms in their implementation [13].

Trigueiros et al. used a machine learning algorithm and attend to which machine learning algorithm is appropriate for real-time HGR. In their research, they used Naïve Byes (NB), k-Nearest Neighbor (k-NN), and Neural Network (NN), where they applied all these methods twice on two different sets of gestures [14].

Wang et al. attempted to segment hand gesture utilizing skin detection in RGB color space, combining achieved color extraction and clustering Y' is the luma component and CB and CR are the blue-difference and red-difference Chroma components (YCbCr) color space. After color image extraction, they continued to edge detection and with the morphology processing fill the binary holes [15].

Zhang et al. used circular gradient edge detection technology to hand gesture segmentation and skin detection technique in HSV color space. They presented a transforming method that can produce HSV color space from RGB and in the HSV color space. After the filtering, they achieved the hand detection and found those points that make the hand region. This was done by utilizing the technology of circular gradient edge detection that contained and filled the holes of binary hand segmentation [16].

2.1. Machine Learning

Machine Learning is an important type of AI used in information technology and computer sciences development. The essential purpose of AI is to optimize the criterion using example data or past experience. In machine learning, two entities - the teacher and the learner, play a crucial role. The teacher is the entity that has the required knowledge to perform a given task. The learner is the entity that has to learn the knowledge to perform the task. We can distinguish learning strategies by the amount of inference the learner performs on the information provided by the teacher. Learning techniques can be grouped into three big categories: supervised

learning, reinforcement learning, and unsupervised learning. The work of this thesis focuses on supervised learning [17].

2.1.1. K-Nearest Neighbor

K-Nearest Neighbor (K-NN) is one of the top levels of machine learning algorithms or data mining algorithms, and it is one of the supervised learning algorithms. K-NN has been utilized in pattern recognition and statistical estimation and it is known as a lazy learning algorithm. K-NN is very intuitive and simple algorithm. If the number of samples is large, then K-NN is a good classification choice. K-NN can classify datasets which have similarity with the k neighbors. To maximize the accuracy and optimize the performance of K-NN classifier, a large number of training samples has to be used [18].

2.1.2. Support Vector Machine

The Support Vector Machine (SVM) algorithm is based, in its simplest form, on constructing a hyperplane that separates two linearly separable classes with the maximum margin. SVM is one of the supervised learning algorithm used for classification. It initially came to the practical implementation in the 1990s. The proper implementation of SVM can lead to high performance in applications [18].

2.1.3. Naïve Bayes Classifier

Naïve Bayes is a statistical classification which predicts class membership based on conditional probabilities. It was proposed by Thomas Bayes and it is considered one of the supervised learning algorithms in machine learning. In the Bayesian model, the nodes are made from the given training data [19].

Bayesian classifiers are statistical classifiers. They can predict class membership probabilities, such as the probability that a given sample belongs to a particular class. The Bayesian classifier is based on Bayes' theorem. Naïve Bayesian classifiers assume that an attribute value of a given class is independent of the values of other attributes. This is known as class conditional independence. To estimate the accuracy of Naïve Bayes (NB) classification

model, a comparison between the test sample known as a label and the classified result from the model can be done. The accuracy rate is found from the test sample percentage that has correctly been classified, and the test set is depending on the training set. The Naïve Bayes classifier has many advantages, namely, it is easy to implement, and it requires less amount of training data than other classifiers to estimate the parameter [19].

2.2. Color Space

In computing images, depending on color expression ways, have some and different color spaces, and each color space has a different color range in hand skin. For hand segmentation procedure, the appropriate color space should be selected. In hand gesture and in the field of skin color detection, most researchers have used RGB, YCbCr, and HSV color space [20].

An RGB color space is popularly used in hand skin detection and has a mixed color space and RGB that is referring to Red (R), Green (G) and Blue (B) primary colors. These R, G, and B can represent all other colors. RGB color space is not utilized in most experiments because digitizing the details is difficult and RGB color space mixes saturation hue and luminance together. Each color channel is highly dependent and correlated, which means it is hard to separate the colors [20].

HSV is another type of color space and it based on Intensity/Saturation/Hue. HSV color space uses Hue, Saturation, and Value to express the colors. Hue is described by the angle which ranges between $[0^\circ, 360^\circ]$ [21].

YCbCr is a type of linear chromaticity/luminance. It is a contributor in the YUV family. In YCbCr, Cb and Cr are 2D independents and in this color space, Cb and Cr are chromaticity's of red and blue colors [21].

2.4. Color Space Analysis and Selection

In the hand gesture segmentation procedure, the value of luminance influences the hand gesture. Therefore, the color space should keep away the luminance effect. In addition, for getting good clustering features the selected color is assumed.

RGB is a model of color space which mixes the three kinds of R, G and B color information. In the color space of RGB, the clustering range varies a lot in the same skin. In the color space of RGB type, luminance and skin ranges are highly correlated. Compared to other color spaces, RGB color space has less clustering futures than YCbCr and HSV color spaces. This information explains that the color space of YCbCr is a discrete space while HSV color space is a continuous space. Color chromaticity's Cb and Cr, and luminance Y obtain the linear transformation of Red, Green, and Blue primary colors [21].

3. HAND GESTURE RECOGNITION

It has been proposed in the literature that covariance coordination can serve as a strong and computationally attainable way to deal with activity recognition. This methodology, which includes figuring the covariance lattices of highlight vectors that speak to an activity, can conceivably be valuable in the 2-D hand gesture recognition model too. In any case, this stochastic methodology requires a watchful determination of elements with a specific end goal to accomplish high order rate [22].

Nevertheless, based on covariance coordination, another methodology has been proposed in the work of Jmaa and Mahdi [22]. Rather than building a word reference of covariance lattices, this methodology is based on investigating three essential components extracted from a picture: area of fingers, tallness of fingers, and the separation between every a pair of fingers. A histogram was utilized and connected to the recognized fingers with a specific end goal to separate the components for digit recognition. By considering the three geometric components, this methodology could give back the fitting hand-digit without pre-computing a word reference as on the account of covariance coordination [22].

Despite the fact that covariance coordination is substantially more adaptable, it can be utilized as a part of an assortment of recognition assignments. This methodology requires a cautious choice of the highlight vectors and its computational expense is conceivably high. Then again, the arrangement that Jmaa and Mahdi proposed is limited to just hand-digit recognition. Notwithstanding, the execution of this methodology is moderately less demanding and requires less preparation. Apart from this technique, there have been various applications that utilize polygon estimation to distinguish convexity focuses for hand-digit recognition [23].

3.1. Sign Language Recognition

Two vision-based sign language recognition structures covering Hidden Markov Model (HMM) were presented in [24]. The first one used a second-individual perspective by a mounted camera, and the second employed the essential individual point of perspective with a camera mounted on a top cautioning by the client, which was utilized for preparing and persistent movement following. Both frameworks utilized a skin shading coordinating calculation for hand

following. When a pixel of skin shading is discovered, the search for tantamount shading zones should begin by checking the eight nearest pixels. While hands are consistently moving, the facial domain was lessened considering the assumption. When hands cover each other in the view of 2D video limitation, the system or the application was not prepared to specific two hands. Whatever point obstruction happened, they basically allocated the whole zone to each hand. Both structures were set up to see American Sign Language (ASL) sentences and erratically perused the kind of individual verb, pronoun, and things enlightening the word [24].

Ong et al. [25] presented a new system that used a course of classifiers to distinguish dim scale pictures from hand shapes to track the hands. First, they assembled different photos from hand shapes. These photos had to be collected by applying the K-medoid batching calculation. Then, to contain two layers of “weak” hand locators, tree structures were encircled to hold the two layers of “weak” hand locators. In the foremost layer, all occasions of hand pictures were sketched out with one agent picture. All confident pictures were picked in the essential layer by the classifiers. After separating photos and labeling of different class types, then they were passed to the second layer. The FloatBoost estimation was used to make boosting in discovering weak classifiers [25].

Cooper et al. [26] used both of beforehand expressed procedures to comprehend a Sign Language Recognition (SLR) plan in a gigantic vocabulary. They had three sorts of classifiers that recognized tab (position), sig (improvement) and ha (strategy) from visemes in the principle layer, which are visual illustrations of talk sounds in the gesture based communications. In any case, it was performing preprocessing of skin division by a Gaussian skin shading model for perceiving skin and an institutionalized histogram for recognizing establishment. After the three segments (sig, tab, and ha) had been evacuated, it looked more than two changed sorts of classifiers catching up on two dimensional highlights in boosting technique, where it included substance classifiers and neighborhood twofold. The helped visemes were collected for creating a combined component vector and in addition delivered to the next layer, in which unusual state classifiers performed word acknowledgment using Markov chains. It is not lively adequate to consider just hands while doing SLR, especially while setting one upstream of pictures since hands often are covered [26].

This issue was conquered in [27] by distinguishing arms and hands meanwhile. In the midst of an acknowledgment, all pixels were doled out for either the establishment model or the extremity model to keep up a vital separation from the dubiousness initiated by hand, upper arm and lower arm obstruction. For the purpose of arm regions, a testing based procedure for single housings was used. Specifically, by considering after the arm plans, unambiguous edges were recognized and also associated together. Most previous investigations of SLR were focused on isolated recordings which were recorded under examination office criteria. They had some issues, for instance, little vocabularies, and there was no sensible way to deal with taking a gander at and measure their execution directly [27].

An assembled broad transparently open database named RWTH-BOSTON-400 was developed in [28]. This database was transformed into a benchmark for a measurable machine elucidation systems and evaluating customized SLR structures. This XML database contained the datasets of Arabic Sign Language (ArSL) circulated by the National Center for Gesture Resources at Boston University and SL. This benchmark dataset contained 842 sentences, two male endorsers, and two female underwriters. By different dresses as well as other setup stances, there were nine-speaker setups. In this research, the author also studied this particular database with some other video standard databases, offering condition to measure head and hand taking after counts [28].

3.2. Glove-based Technique for Gesture Recognition

An application of a glove-based method for ASL fingerspelling acknowledgment was reported in [29]. Here, the implementation had twenty-six ASL alphabets, and two additional signs available on the PC's keyboard, namely the "space" and the "enter" signs, which were seen logically. It gave an interface to customers to send to a talk synthesizer and to edge words/communications. The structure included a little scale controller, five point of Micro Electro Mechanical System (MEMS) and the Accele Glove twofold center point accelerometers. The finger postures gave by the Accele Glove read by the scaled-down scale controller and sent groups of 10 bytes to a computer. In a midst of setting up, a three-level different leveled classifier was created and a plan of position parts was isolated [29].

Tweaked with the readied classifier, the scaled-down scale controller recognized the finger-spellings, and after that would send the relating ASCII code to a voice synthesizer so that the structure could truly recognize the letters. This structure accomplished a precision of 100% for twenty one out of the twenty six letters, and the letter “U” was the most negative situation, with an accuracy of 78%. Considering the same thought, the research of [30] added another SLR structure for Vietnam Sign Language (VSL). The authors included one or more sensors to the back of the hands for upgrading the strategy. A substitute portrayal for letters was introduced, in which all letters would be divided into three dusters as shown by X-turn estimation of the palm [30].

A three soft rule-based system was created for more requests without gathering get-ready tests. There were five levels to measure bowing or flexing of fingers, namely Very-Low, Very-High, Low, Medium, and High. In this way, as a part of programming, a course of action was used based on “if-then-else” enunciations. It exhibited promising results in acknowledging the accuracy where twenty out twenty-three letters were attempted and a precision of 100% was obtained. The most cynical situation was again with the letter “U” which had an exact of 79% accuracy [30].

Another data glove device presented in [31], in a similar manner, the force that fingers covered with glove-based technique associated thing as well as giving finger positions were addressed. The glove was secured and made of cotton. Flexsellsors, as finger position sensors, were attached to the glove by Cyanoacrylate glue. The data taken by position sensors was sent to a computer via a method suitable for two small-scale controllers, namely the “slave” littler scale controller and the “root” scaled down-scale controller. To translate the position information, the computer used a specialized framework. The thumb was joined to the strain gage power sensor; its yield voltages were comparing to the associated power. To control the expansion of the force converter, sensor, and a present source were used. The computer ran a modification program for two position sensors and a force sensor, and to disentangle the results, a short time later was set up [31].

To manage virtual reality applications, this data glove presented a good approach. By captivating eventual outcomes of the measure of force, one would utilize to squash or get things. One may scrutinize which paying little mind to the formal of glove-based structures. The glove contraptions are unfeasible in light of the fact that they are regularly ghastly. Since controller chips and different sensors are required, for no matter how you look at it, the expense here is another issue [31].

Kenn et al. devised a way to deal with joint glove-based products towards various applications at the assistance to a setting platform [32]. The material of the glove and the consolidated hardware contraption were cool in appearance, as well as could perform under three applications. These were represented by to move/ select /zoom components of an aide to investigate towards a remote control at presentation, and also to direct a toy robot to push left/right and forward/in reverse. Signals were fundamental yet adequate in speaking and similar application applications. One problem was found that is this device can simply recognize signals in the Y and X, but it cannot identify the movement in Z center point, for instance, the gathered “yaw”. Despite achieving a wearability fit, cool appearance and light weight, the reliability of acknowledgment is surrendered. The glove techniques portrayed so far at a very basic level that works with 20 information instances. In any case, bona fide applications incorporate motions in the 3D space, the example of glove-based systems is showing 3D acknowledgment and the diminishing of expense without surrendering exactness [32].

Kim et al. used a data glove called KHU-I which was added to a 3D hand movement taking after and signal acknowledgment system [33]. A PC with a data glove interfaced by a method for contraption of a Bluetooth was used. It viably completed hand movement taking after for instance clench hand holding, hand extending and bowing. A standard based figuring was used as a piece of the essential HGR at two assorted exact locations, namely vertical and even. Three signals (paper, scissor, and shake) were attempted with an accuracy of 100% obtained for 50 trials for each. The remote transmission and the acknowledgment in 3D were incredible upgrades. Be that as it may, they achieved time delay. In any case, the attempted motions were too much clear and unnecessarily few, making them incomprehensible and difficult to show the

healthiness of this system high acknowledgment precision with a prudent visual movement data glove was shown in [34].

A singular channel video was used from the glove contraption as opposed to the consistently used movement distinguishing fibers or multi-channel recordings, with an amusement figuring to conform for insufficiencies of single-channel recordings. Slim “var-sort” optical pointers were attached to the glove to keep up a key separation from a high repeat of optical occlusions. The used camera for catching hand movements was a monocular camera. A visual analyzer figuring distinguished the recovered 3D positions of fingers, optical markers and joints. Three classes of circumstances (right/left, numbers, snaps, and the OK sign) were duplicated and considered along with the 3D pictures in a MATLAB environment. The figuring time was effective to picture uproar and goof extents. The benefit of this strategy is that the materials for apparatus were moderate and it had enduring preparing low estimation and time botches. In any case, it was not a continuous system [34].

3.3. Gesture Recognition

The hands are hard to be segregated from the face on the account of their practically identical skin tints if a shading based division is used. Besides, when the establishment is non-uniform or the lighting conditions change, its execution continues. Due to its physical contact, the data glove procedures that give hand positions may be a respectable tactic to deal with shading based division amplification. Nevertheless, they cause uncomfortable customer experience. Fortunately, another contact-less approach turned out in the past, around 10 years ago, that used significance discontinuities to autonomous hands recognition from the establishment. Thusly, significance based systems keep up a key separation from each one of these issues determined already.

Nanda et al. [35] displayed a system for tracking hands in significantly messed circumstances. This hands tracking system employed 3D significance data taken from a sensor relied upon the Time-of-Flight (ToF) rule for finding shading and significance information by using the same optical center in same time. The potential fields of possible face or hands shapes were figured by two main computations: getting potential fields by using partition change and

weights and bowl of interest with k-segments based potential fields. The structure was attempted in hand taking after and head taking after on 10 people with awesome results. The structure could track hands to see direct developments like “stop” and “step back” and with some obstructions. In any case, since hand shapes are moved, it isn’t appropriate for steady systems so that a significant measure of structures are required for affirmation [35].

Antonis et al. suggested a 3D hand taking after technique using the action of two video streams of a stereoscopic course [36]. It consolidated a 3D hand following and shading based, and it could continue running dynamically. 2D shading based hand trackers were used to separate hand blobs in both video streams. After that, replanted together by modifying the figuring. Next, hand shapes were changed and balanced in the 3D space. This system was associated with a couple of utilizations. One examination was by hand signal working with a CD player for recognizing the type of the hand and pointer. The limit of planning consistently is influenced. In addition, the necessity for an arrangement that fabricates system versatile quality and the surveys significance data using the stereoscopic structure is genuinely noisy [36].

Van et al. used a ToF camera as opposed to stereoscopic cameras to update the affirmation [37]. The ToF camera here had a low resolution (176 x 144 pixels). It was coordinated with an RGB camera that had a higher resolution (640 x 480 pixels) for hand area and was used to get significant pictures for the division. The RGB and ToF cameras were adjusted towards the beginning, and an edge division was portrayed to hurl the established pictures as showed by the significance data. The remaining pixels were encountered a skin shading conspicuous verification to get hand information. The skin shading used for the area was picked by a pre-readied adaptable skin shading model, which was upgraded with shading information taken from the face. Three situations were evaluated near to the area: the hand secured with the face, the hand was separated from the face and the face was behind the analyzer [37].

3.4. Kinect Techniques Related Studies

Immediately after the release of Microsoft Kinect in November 2010, a couple of stimulating affirmation structures considered this device were made within eighteen months. The Kinect

camera has a great quality and its USB camera and consequence camera are both 480 x 360 pixels; those are truly satisfactory under numerous circumstances.

Yan et al. developed a movement affirmation structure using significant material provided by the Kinect and executed in media player application [38]. This structure could see eight signs to control the application of media player, with the greatest chaos degree of 8.0%. The estimation for hand gesturing taking after was initially aimed to first discover the hand-waving developments. This was done considering the suspicion that a customer tends to initiate movement associated with such a development [38].

A reliably flexible mean development estimation was associated with tracking the hand gesture. This was done by using the significance property, and it upgraded the significance histogram by a separate classing. The hand gesture was broken down in a 3D highlight vector, and the sign was seen by an HMM. This building establishes the importance by using Kinect for measuring the confirmation as a part of a contact-less User Interface. The past structure was prepared to catch fingertips; thusly, it was confined to see just the development in movements or like- movements, down/up, right/left, and backward/forward [38].

Rahej et al. presented a method to track the centers of palms and fingertips using Kinect [39]. This method associated a threshold to obtain the significance of hand districts for the division. By then, the palm was isolated and subtracted from the hand, so that in the photo just the fingers were left. Under most circumstances, when the hand was before the customer with the shallowest significance, the fingers should be closest to the Kinect. In this way, by choosing the base significance, fingertips were found. And the point of convergence of the palm was controlled by discovering the most compelling of division inside the photo of the hand. When fingers were expanded, the precision of perceiving fingertips was around the degree of 100% accuracy, and that of the palm base was 90%. However, this method did not try inspecting movement affirmation [39]

4. HAND DETECTION METHODS

Hand location and following hand identification are a subject which has a long and a broad assortment and history of scientific research and applications. For instance, HCI, SI mediators, human position affirmation, and perception. In the early stage of development, hand location framework required tinted gloves or markers to make the affirmation less requested. Later, systems used low-level segments, for instance, shading (skin based discovery) or shape. A huge recent researchers' work on hand discovery in recordings has been completed in 3D [40].

Significance data provided by significance camera(s) is mainly used. As one in a few late 2D hand discoverers for recordings, the hand marker proposed in [41] for manhandle stream field. By preparing the point size of the stream field, they proposed the assumption that the development discontinuities. Then, taking into the account a straight channel using a method for Support Vector Machine (SVM). This development broke the size sign exactly to the hands. Hands were recognized as districts and also had the greatest reply from the locator at all packaging zones over a discrete plan of hand presentations [41]. In this work, the outcomes of hand location were simply used as additional prompts for members, since their last explanation behind the existing was not the hand discovery rather stomach range stance estimation.

The greatest of hand recognition followed methodologies acknowledges that in a photo diagram hands are the most moving things. A system was proposed to use a transient divert to pick the greatest likely bearing of hand regions among different competitors procured by "square stream" planning [42].

A skin shading based tracker which allowed the utilization of additional data prompts, for instance, picture establishment model, expected spatial region, speed, and condition of the took after and the recognized segments were proposed in [43]. The advantage of these trackers is that they can track hands consistently. Anyway, their trackers simply work under obliged circumstances where the establishment are unaltered, so that basically subtracting the establishment can bring them sufficient flags to find the most moving things which imply the hands [43].

4.1. Computer Vision Techniques for Hand Gesture Detection

There are three layers of hand interactive systems which consist of detection, tracking, and recognition. As it can be seen from Figure 4.1, the task of detection layer is to define and recognize the appearance of objects in the view of the camera(s). After detecting the objects in the view of the camera, the tracking layer uses multi-view inputs to track the objects in the camera's viewpoint. This tracking layer helps the approximation of the positions and features of the objects in the view of the camera. Finally, recognition, which is the last layer, recognizes the objects. This layer uses the task results processed in the detection and tracking layers, and groups those task results to different gesture labels.

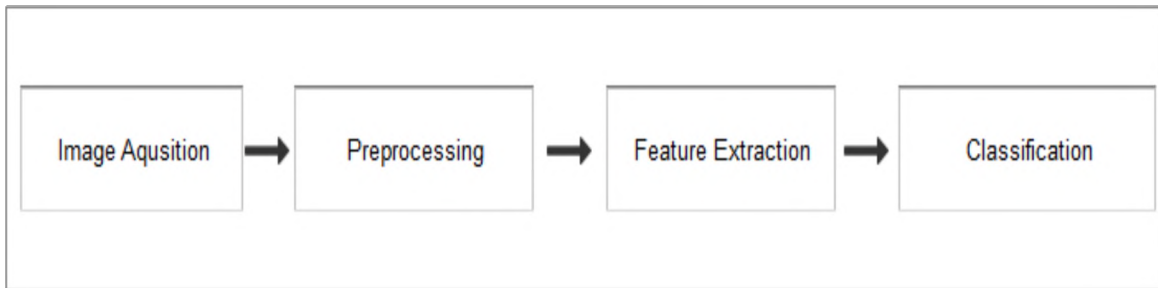


Figure 4.1 System overview

4.1.1. Detection

The key step in movement affirmation systems is the division of the related picture districts and the recognition of hands. This division is urgent in light of the way that it separates the errand crucial information from the photograph foundation, before passing them to the detection and consequent steps. Numerous proposals have been suggested in the literature which utilize a couple of sorts of visual segments and, when in doubt, their mixture. Such components are skin shape, shading, anatomical models and the development of hands [44].

4.1.2. Color

Skin shading division has been applied by a number of techniques for hand recognition. An imperative decision against giving a model of skin shading is the decision of the shading space to be used. A couple of shading spaces have been suggested contain RGB, standardize HSV,

RGB, YUV, YCrCb, etc. The luminance parts of shading are normally seen as best since shading spaces proficiently detaching the chromaticity [45].

This is a result of the route that uses chromaticity-subordinate parts of shading only, some level of light changes may be refined. An evaluation of skin chromaticity execution and a review of various skin chromaticity models are provided in [45]; the interested reader may refer to it for further details. To produce an insurance against light variability, a number of techniques work in the HSV, YUV shading spaces, or YCrCb, to induce the “chromaticity” of skin (or, generally, its maintenance territory) instead of its unmistakable shading regard. They frequently arrange the luminance fragment, to eliminate the effect of shadows, lighting converts, and likewise alterations of presentation of areas of a skin as for the light source(s). The remaining two-dimensional shading vector is practically reliable for skin areas and a 2D histogram of the pixels from a zone including skin shows a strong peak at the skin shading [45].

4.1.3. Shape

The trademark condition of hands has been proposed to recognize them in pictures in different ways. Huge information can be obtained by basically eliminating the states of articles in the photo. If adequately distinguished, the structure addresses the condition of the hand and in this way lighting and shading affect the shape of the hand. The expressive power of two-dimensional shape can be demolished by obstructions or hoodlum points of view. Propelled post-taking care of philosophy is required to extend the faithful nature of such an approach. In this spirit, edges are every now and again joined with skin shading and establishing subtraction/development prompts. The 2D/3D drawing systems of the customer’s hand are directly removed from the structure by performing a ceaseless edge discovery in the photo and tolerating a uniform establishment. Tests of the usage of structures as parts are found in appearance-based techniques and both models [46].

In [47], a finger and arm joint applicants were picked through the gathering of game plans of parallel edges. In a more overall approach theories of hand, three-dimensional models are calculated by first mixing the edge photo of a three-dimensional show and differentiating it

against the obtained edge picture. To organize a model with the edges in the photo, topological descriptors have been used.

The shape setting descriptor is suggested in [48]; it depicted a particular point territory on the shape. The shape was a histogram of the relative polar headings of each other's point. The descriptor has been associated with a collection of articles affirming the issues with confined establishment mess. David and Bobick proposed that each topological mix of four centers could be considered in a voting grid and facilitated correspondences were set up using a ravenous count [49].

The approach presented in [50] suggests that data hand pictures should be guided towards a planar and homogeneous establishment. The light is such that the hand's shadow is hurled on the foundation plane. By relating high-contort parts of the hand's chart and the shadows, hugeness signals vanishing focuses are cleared and the hand's position is evaluated. Certain techniques concentrate on the particular morphology of hands and endeavor to remember them considering trademark hand shape segments, and occasionally, fingertips [50].

The methodologies reported in [51, 52] used shape as a sign of fingertip acknowledgment. Another strategy that has been utilized as a part of fingertip area is the organization sorting out. Game plans can be pictures of fingertips, fingers or dull 3D tube-shaped models. Such representation arranging techniques can be updated by utilizing extra photograph highlights similar to the shapes.

The format planning framework was utilized in a similar manner in [51], with photos of the top point of view of fingertips as the model. The pixel, realizing the most paramount association, was picked as the position of the goal thing. Besides, being computationally immoderate, design organizing can adjust to neither scaling nor turn of the goal thing [51].

In [52], the fingertip of the client was seen in both photographs of a balanced stereo pair. In these photographs, the two focuses at which this tip shows up build up a stereo correspondence, which is used to gauge the fingertip's position in 3D space. Along these lines, this position is used by the structure to assess the division of the finger from the work zone and, consequently,

understand whether the client is touching it. A structure was depicted for taking after the 3D position and presentation of a finger utilizing a few cameras [53].

Taking after depends on the after joining distinctive wellsprings of data including stereo degree pictures, shading division and shape data. Stereoscopic data is utilized to give 3D positions of hand centroids and fingertips, besides to reproduce the 3D condition of perceived and took after hands progressively [54].

4.1.3.1. Learning Identifiers from Pixel Values

Vital work has been done on discovering hands in weak level pictures considering their appearance and creation. The sensibility of various solicitation frameworks with the last target of perspective self-administering hand position confirm is provided in [54]. Several methodologies attempted to perceive hands in light of hand appearances. The hand appearance separates more among hand signals than it changes among various individuals performing the same development. Still, modified highlight choice constitutes a basic impairment. A couple of papers considered the issue of highlight extraction and the choice with bound results as to hand acknowledgment [55].

The work of [56] breaks down the separation between the most secluding parts and the most expressive segments in the depiction of advancement that contains signals. It is argued that the most expressive parts may not be the best for strategy. In light of the way the fragments that depict some basic combinations in the class are, frequently, superfluous to how the sub-classes are detached. Most secluding fragments are picked by multi-class, multivariate separate examination and have an unmitigated higher capacity to get basic contrasts between classes. Moreover, their examinations displayed that most confining fragments are better than the most expressive parts in altered highlight determination for solicitation [56].

All the additionally beginning late strategies, in light of the machine learning approach called boosting have demonstrated, to an incredible degree, strong results in face and hand area. In light of these outcomes, they are watched out for more detail underneath. Boosting is a general method that can be utilized for updating the exactness of a given learning calculation. It depends

on the fundamental that an exceedingly right or “solid” classifier can be determined through the quick blend of different all things considered mistaken or “fragile” classifiers. With everything considered, an individual fragile classifier is required to perform just irrelevantly superior to anything sporadic. As proposed in [57], for the issue of hand acknowledgment, a weak classifier may be a vital identifier in the context of critical picture square complexities enough enlisted utilizing an essential picture.

A learning methodology for finding proper social events of slight classifiers was given in [58]. For setting it up, an exponential hard work may be used that can model disturbed labels. The procedure uses an available set of pictures that includes positive and negative diagrams (hands and non-hands, for this condition), which are connected with taking a gander at names. Sensitive classifiers are consolidated dynamically into a present strategy of effectively picked frail classifiers to decrease the upper bound of the arranging mishandle. It is comprehended that this is conceivable if powerless classifiers are of a specific structure [58]. And also connected hand with face and observed acknowledgment are producing more readable results. In any case, this technique may accomplish an over the top number of delicate classifiers. The issue is that it does not consider the clearing of picked slight classifiers that no more added to the revelation method. The FloatBoost include was proposed in [59].

It opened up the central AdaBoost calculation, in that, it expels a present slight classifier from a solid classifier on the off chance that it no more adds to the decrease of the plan blunder. This result should be considered in a more wide, thusly, a more profitable course of action of frail classifiers. In the same manner, the last identifier can be secluded into a course of strong classifier layers [60].

This different leveled structure is incorporating a general identifier at the root, with branch center points being logically more appearing particular as the significance of the tree increases. In this approach, the greater the significance of a center point, the more specific the planning set gets the chance to be. To make a checked database of getting ready pictures for the above tree structure, a modified methodology for performing social occasion of pictures of hands at the same position is proposed, in the perspective of an unsupervised bundling technique [60].

4.1.3.2. 3D Model-based Recognition

Many techniques use 3D hand models for real time hand gesture recognition. One of the advantages of these methods is that they can achieve view free identification. The used 3D models should have enough degrees of adaptability to conform to the estimations of the hand(s) present in a photo. Assorted models require particular picture segments to fabricate highlight model correspondences. Point and line segments are used in kinematic hand models to recover edges encircled at the joints of the hand [61].

Hand positions are then surveyed given that the correspondences between the 3D model and the watched picture parts are settled in. Distinctive three-dimensional hand models have been suggested in the literature. In [62], a full hand model was proposed.

The model had 27 degrees of adaptability (DOA) (6 DOA for 3D zone/presentation and 21 DOA for articulation). A “cardboard model” was utilized in [63] where each finger was addressed by a course of action of three related planar patches. Apart from that, a 3D model of the arm with 7 parameters was utilized in [64].

The 3D model was further developed by using 22 degrees of adaptability for the whole body with 4 degrees of a chance for each arm [65].

The customer’s hand was exhibited extensively all the more fundamentally, as a verbalized rigid article with three joints required by the essential pointer and thumb [66]. Edge highlights in the two photos of a stereoscopic pair were identified by removing the presentation of amidst joints of fingers [67]. These are thusly utilized for model based following of the hands. An artificial neural framework that is set up with body points of interest was utilized for the recognition of hands in pictures [68]. The fitting is guided by qualities that attract the model to the photo edges, balanced by various forces that tend to spare movement and value among surface centers [69].

The strategy is enhanced with anatomical data of the human hand that is joined into the model. Moreover, to fit the hand model to a photo of an honest-to-goodness hand, trademark

concentrates on the hand are recognized in the photos, and virtual springs are construed, which pull this trademark centers to target positions on the hand model [69].

4.1.3.3. Motion

For hand detection, a few methodologies are used, such as motion. One of the very controlled setup demands is the motion based for the detection of hand. A hand movement occurs when you just move in the picture. Indeed, recent developments conducted on hand gesturing suggest that the motion of the hand is just the movement occurring in the environment of the image. In most modern approaches, the information of motion is concatenating with extra visual signs. In the situation of static cameras, the problem of motions estimation decreases to that of subsequent subtraction and background maintenance [70].

4.1.3.4. Tracking

The frame-to-frame or tracking, the correspondence of the hand segmented features or areas, is the step number two in the process of recognition towards accepting the perceived movements of the hand. Robust tracking importance is twofold. One: It provides the inter-frame linking of finger/hand forms to routes of features in a time giving rise. These routes transport essential data about the gesture and might be used either in a raw form or after more examination (e.g. recognition of a certain type of gesture of hand). Two: In methods of model-based, and these steps of recognition, it offers a way to maintain estimates of features and model parameters variables that are not straight visible at a confident moment of time [71].

4.2. Arabic Sign Language Recognition in Real-Time

Real-time Arabic Sign Language (ArSL) image-based recognition system can be composed of five steps, namely, image acquisition, preprocessing, segmentation, feature extraction, and classification. The input for image based SLR for Arabic language applications is a static image or a sequence of signs in a video. Here, the signer point is the space between one sign and another. An important advantage of the image-based ArSL recognition system is that the user is accepted as a signer without using the data glove device. This contains lighting condition, and the background of an image, hand and face segmentation along with additive noise in each of these types. However, the segmentation of faces and hands are computationally uneasy, yet, the

latest algorithms and computing abilities to perform this segmentation have made it possible in real time [72].

4.2.1. The Importance of Sign Language

Sign language is the principle method of correspondence or listening to the disabled users. It is truly a quick and inexpressive method for correspondence. It is actually becoming a joining of hand shapes, development of the hands, arms and the whole body. It investigates the brimming with outward appearances to full exhibit the speaker's contemplations. This language is utilized by making contact with all people or can be a less trouble for human beings to understand signs anywhere and anytime, thus, the sign language was originally created. With complex spatial linguistic uses, sign language is, to a great degree, not the same as the sentence structure used in spoken language. This is due to the tremendous choice of sign languages being utilized all over the world. A few sign languages have, as of now, already been conceded lawful recognition, and measures of different sorts of sign language don't have status or whatsoever [72].

4.2.2. Sign Language Etymology

Sign languages are unlimited. They are not hard languages and they are not held over the panel misunderstandings. Yet, they're most certainly not real languages. There are delegated sign languages have each etymological part that is required as genuine languages. SL is not emulated, as it's the misguided judgment, however, it is viewed as ordinary and self-assertive. It has more processing strides across the board in sign languages rather than spoken ones, which do not require a visual version of the oral form [73].

SL owns one of the structures of the hard language that can be used in examinations, including any kind of subject. It incorporates the company of rudimentary and negligible units into a significant semantic unit. Sign languages include their hand shape, introduction, area, development, and expression. They are connected with hard of hearing sign languages contains the broad use of classifiers, a major measure of expression and a topic comment linguistic

structure. Novel semantic elements are rising up the sign languages ability to pass on, which implies in differing segments from the visual territory [73].

4.2.3. Order of Sign Language

The undeniable reality of sign languages is that they are conceived with hard of hearing groups such as typical individual languages. They differ from the normal individual languages and have their other structures, acting as normal structure of language. Signed languages might be the term for their surroundings, and better to comprehend their discretionary for spoken language, that signed modalities of spoken languages. And afterward, they have a place possess language such as signed to connect to users spoken languages. For illustration, almost all of signal language encoding of English to compare with this particular language. Therefore, out of insufficient phonetic research, by looking at their genetic virtually identical between sign languages and open information, sign languages assume basic part of their brain needs through movements of the hand [73].

As of late, applications to learn sign languages to help all people to communicate are being developed. Exactly, how to upgrade the ability of individuals to discuss easily with signed languages as they've been selected for them, due to the inability to properly speak in a physical way. This will be known as infant Sign. Near utilize of sign languages with a considerable measure of non-hard of hearing youngsters or handicap would be a powerful communication that worth the discussion. Presently, ordinarily, utilization of sign languages is full inside the psyche, specifically into general languages where individuals can easily keep in contact with the outside speaking individuals [74].

4.2.4. Hand Gesture Recognition Challenges

Like many other systems, hand gesture technologies have many challenges. These challenges start with the illumination variation condition. The changes in light conditions are badly affecting the region selection of extracted image in HGR. Another problem is the rotation, which occurs if the hand moves to rotate for any direction in the scene. Also, the background is considered as a problem to the hand object, in the sense that it has other objects in the scene.

The background may produce a problem of misclassification, especially if the background contains the skin like colors. The scale is considered as a challenge in HGR as well. This problem occurs when the gesture image has different sizes of the hand pose. Finally, the translation challenge, where a problem appears when there is a variation of the positions of hand in different images, leads to an error in the reproduction of features [74].

5. THE PROPOSED METHODOLOGY

The proposed method of this thesis is built to recognize digits from 1 to 9 and symbols used in ArSL using supervised learning and libraries of an RGB camera with Kinect sensor. The system has two cameras, one of them is the RGB camera and the other is an Infra-Red (IR) camera. However, this research focuses on the RGB camera. The developed system is shown in Figure 5.1.

A computing system, a standard PC, as well as a list box that allows the user to choose either PC camera or any USB camera, are used. The used PC runs with Windows operating system and the used development environment is C# (Microsoft Visual Studio) provided with OpenCV 3.2.0 and EmguCV libraries.

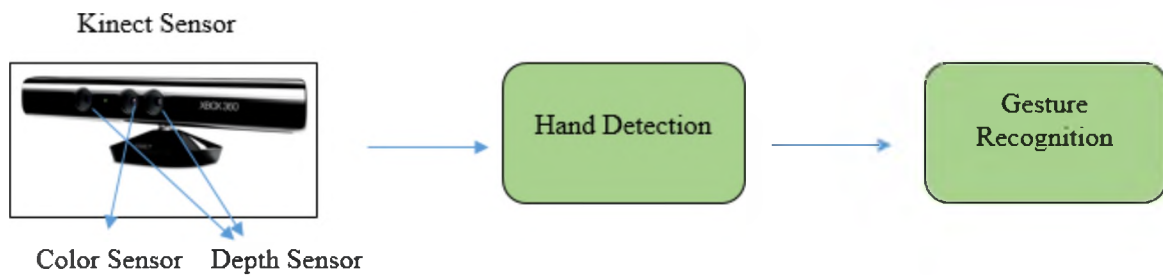


Figure 5.1 Framework of the proposed gesture recognition system

5.1.The Proposed System's Implementation

For recognizing signs and symbols in hand gesture recognition, it is needed to create a flow chart to elaborate how the system and application work. This flowchart is used for developing the proposed application for hand gesture recognition as shown in Figure 5.2.

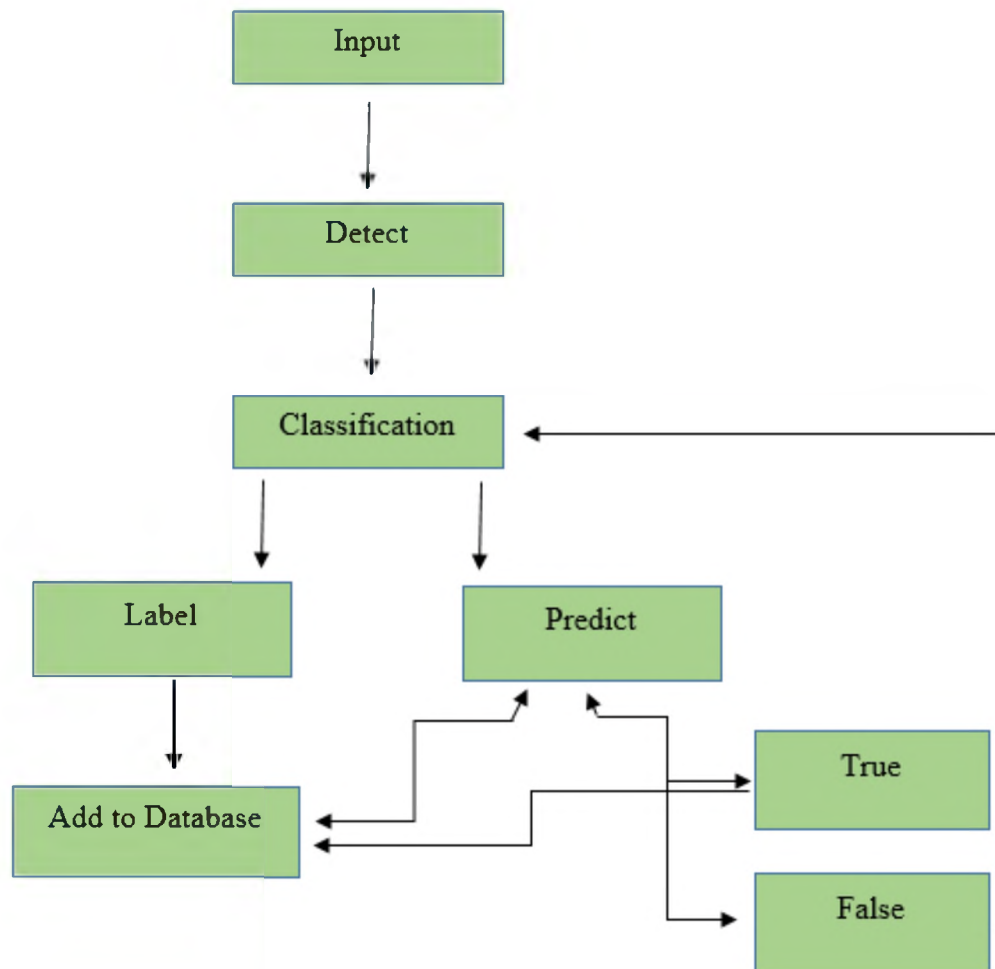


Figure 5.2 The flowchart of the developed hand gesture system

5.2. Graphical User Interface

A Graphical User Interface (GUI) is developed for creating a convenient use as well as a user-friendly environment. The GUI includes options for the user gesture capturing after recognizing the captured images. The output gesture, which will be roughly the same as the sign language, demonstrated by the individual is shown on the screen.

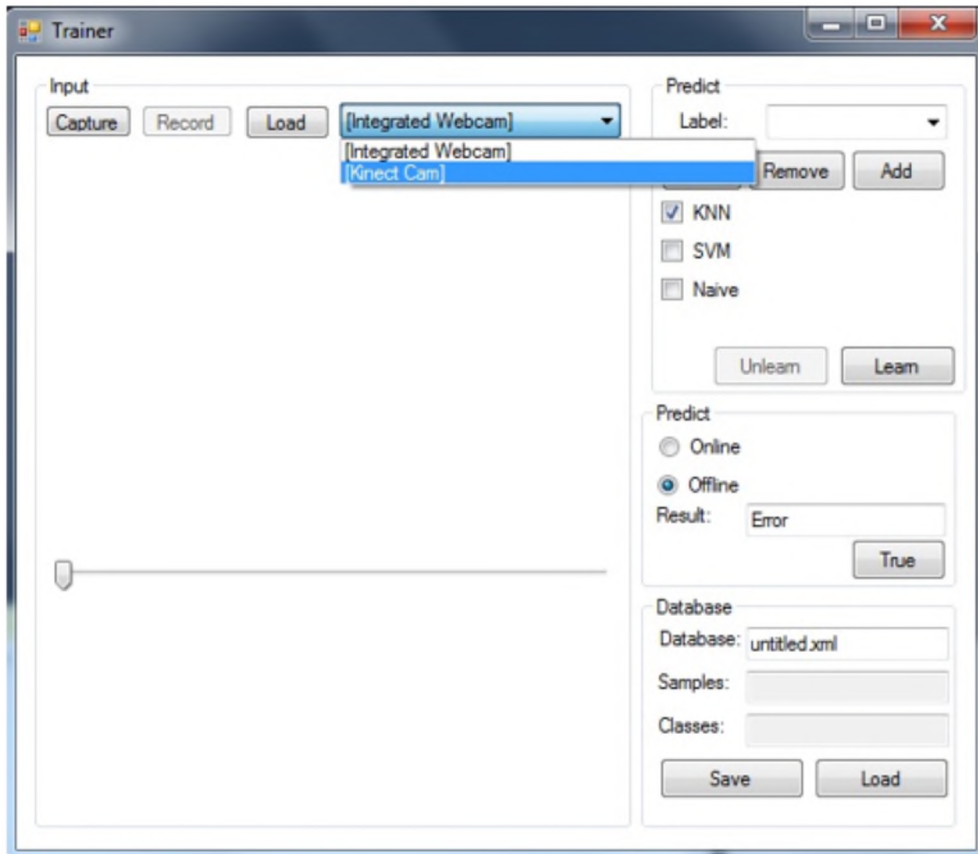


Figure 5.3 GUI for hand gesture application

And to know how the system works, a step-by-step classification methods guide is created for a more accurate explanation. This also displays how to operate the training data and go through all other steps until the last needed step, where the data gets examined. Figure 5.3 is the Graphical User Interface (GUI) for the Hand Recognition system from start to end this process Recognition, and Figure 5.4 Show the processed system implementation for Hand Gesture Recognition in this thesis.

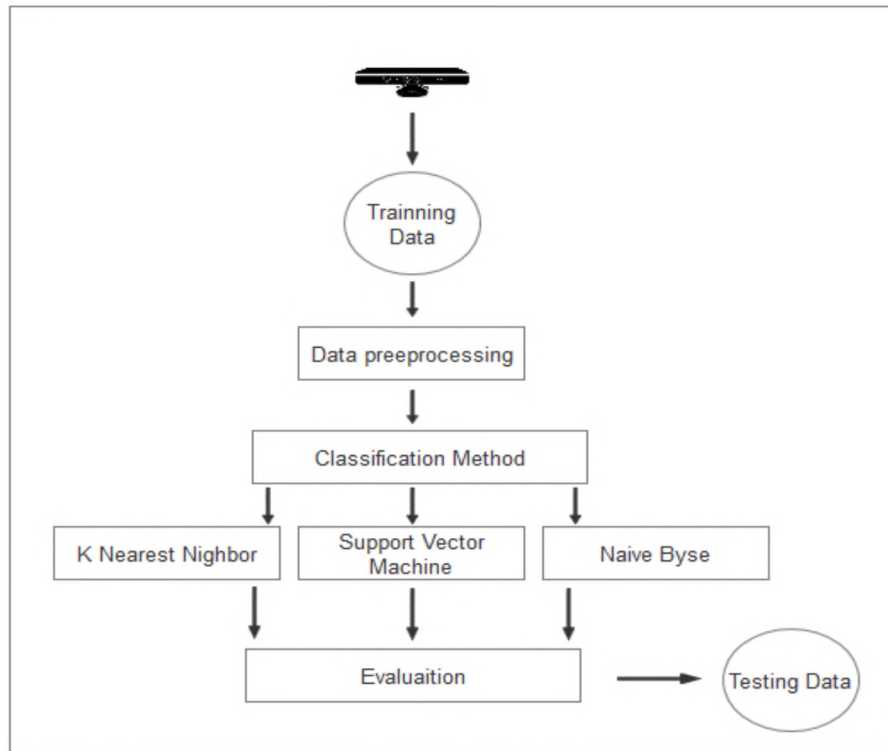


Figure 5.4 The proposed system's implementation

5.3. XML Database

In the world of data exchange, Extensible Markup Language (XML) is considered as a powerful and special database. An XML database has been created for the developed system. This database is important, as it assists extracting the needed details from an XML document and moves them to permanent stores quickly and easily. This application deploys the EmguCV library for the used XML which is written in the following namespace:

`using System.xml.Serialization;`

This XML database can save the trained data that has been labeled and give more than one sample per class. Thus, these samples can be loaded and saved in the database any time needed for testing them and applying gesture recognition process.

5.4. Image Acquisition

The camera is put towards the person, known as a signer, to capture the real-time video sequence. The signer sets the front view of his/her hand towards the camera. The acquisition of the image is being done after the hand is captured in front of the camera's sensor, and each video is converted to some frames. Figure 5.5 shows the image acquisition description of the designed ArSLR system [74].

According to the proposed method, the static image and the real video images are added as a sample. These include a collection of captures of hand sign positions to recognize gestures of humans using different classification methods available in data mining algorithms, such as SVM, NB, and K-NN. Then they are all compared to find the optimal classifier. Finally, the performance of each classification method in this study is computed.

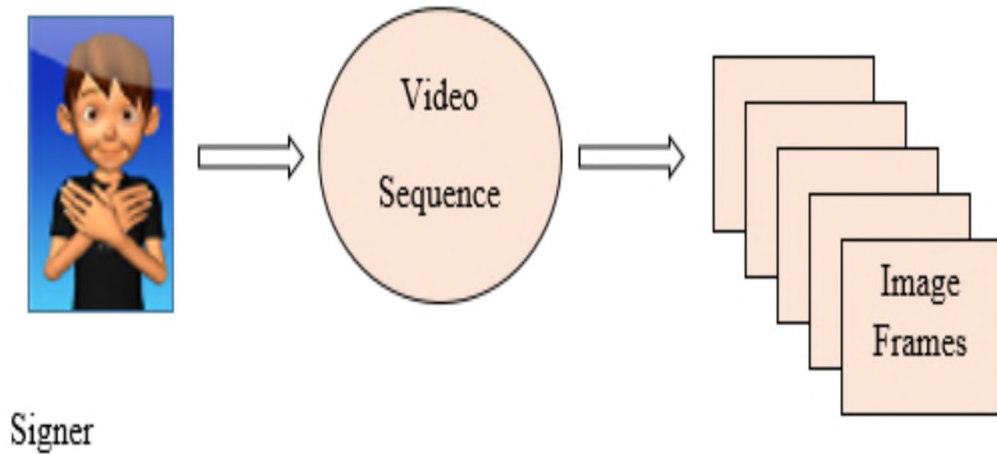


Figure 5.5 Image acquisition block of the automatic SLR system design

The used signs and symbols in the study's dataset compute the numbers (1-9) and three other signs in the Iraqi culture as shown in Figure 5.6.



Figure 5.6 The tested gestures in the proposed system

The setting is established as follows: first, a single Kinect camera is used with the user standing in front of the camera and the distance between the camera and the floor is 1 meter and the distance between the person and the camera is around one meter as well.

5.5. Data Preprocessing

In data preprocessing, local changes of an image by removing noise and digitization errors do not convert the essential image information and scene. The preprocessing is very important in this thesis for recognizing the numbers and symbols correctly and accurately. Various factors that affect preprocessing such as the background, illumination, camera parameters have been taken into the account. The first important step in preprocessing is filtering, as shown in Figure 5.7. To remove the noise in the image scenes, a moving median filter or average is used, and the next step in preprocessing is the background subtraction forms.

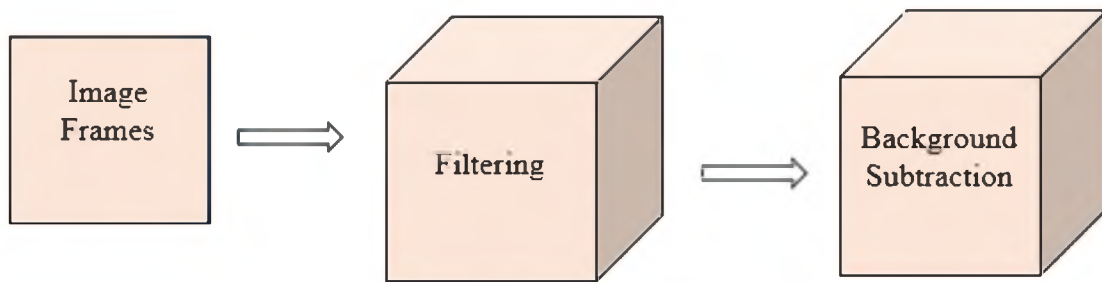


Figure 5.7 Preprocessing of the ArSLR system design

In this study, the preprocessing step uses a small neighborhood of a pixel in an input image to get a new brightness value in the output image. It consists of segmentation, and it is a process of converting or changing RGB image to a binary image. Due to the generated noise, a Gaussian filtering process is used to remove the undesired noise and also it helps to get a complete and filtered contour of the gesture. Here, the output is a black and white image which uses the steps like RGB to gray conversion thresholding and filtering, as shown in Figure 5.8.

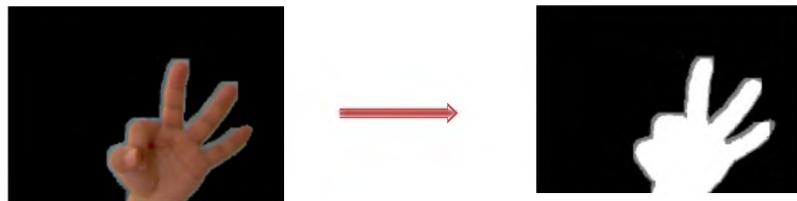


Figure 5.8 Converting RGB image to gray

5.6. Data Training and Testing

In this experimental work, all data mining and classification methods such as K-NN, SVM, and NB are used to train the system for the recognition or classification of human gestures for (1-9) numbers and three other signs in the culture of Iraq. To obtain training data, the human hand should be kept stable in front of the camera to capture the hand image as illustrated in Figure 5.9.

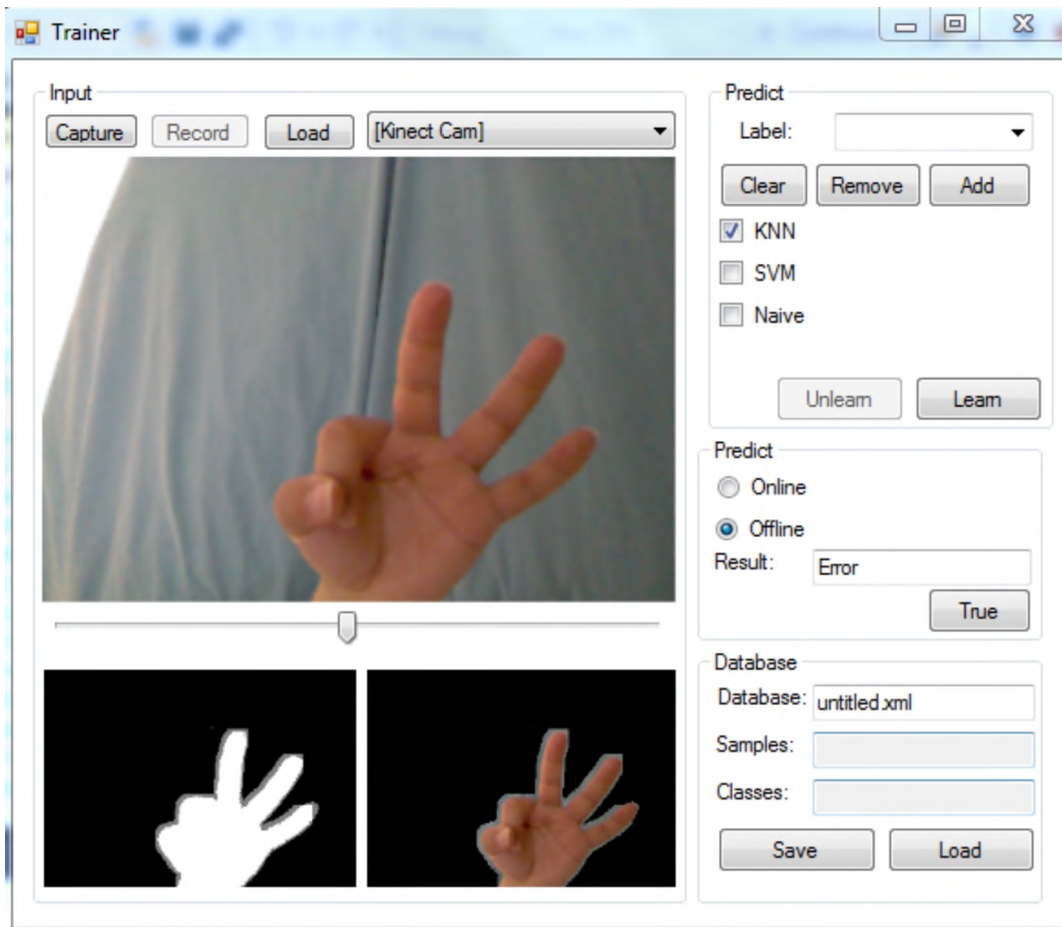


Figure 5.9 Data training and testing procedure

After the training data is obtained, another process is started, that is, the recognition process using the mentioned classification methods. All training imaged information is saved in the XML database, where the recorded and captured images are added to the database which are already in the database with proper labels. The images are recorded from different individuals in order to achieve the final recognition process with different data of hand gesture. Figure 5.10 shows the different training samples of the hand.

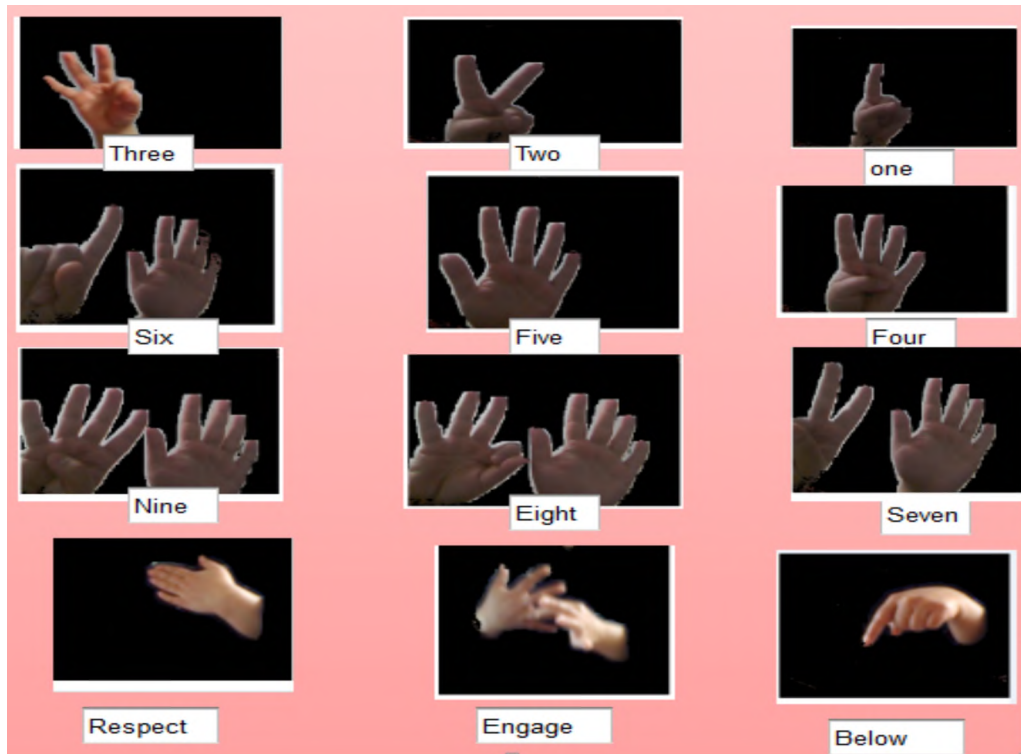


Figure 5.10 Examples of the 12 different gestures to be recognized

5.7. Hand Detection

By using preprocessing steps and filtering techniques, the image becomes equal in intensity and more noticeable. The EmguCV library is used to detect an image from a captured image found in the training data. From the first step of the recognition process, detected images are achieved in real time obtained from a Kinect camera. The detection of the hand is done automatically using the method of skin detector for image color space (RGB, HSV, and YCbCr). In the detection process, the hand is represented by white color and the background is represented by black color, as shown in Figure 5.11.

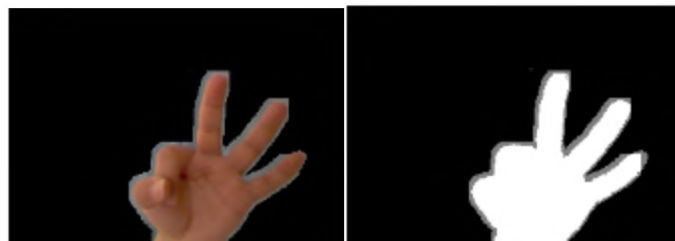


Figure 5.11 The detected image

5.8. Hand Recognition

In this study, three methods SVM, K-NN, and NB are chosen for all classification process. These methods are chosen based on the review of the literature. The fact is that each of those selected methods for classification purpose is effective to hand gesture recognition and sign language recognition applications. The recognition process comes after the detection of the hand gesture. After capturing the hand image in front of the camera, accomplishing the preprocessing and running a complete detection is done next. One of the classification methods SVM, KNN and NB should be chosen; based on that the learning process of the application for the hand sign recognition is done.

Once a new capture is taken again, the hand sign that is captured is then processed in the application with a machine learning algorithm in order to find any match in the database. A true sign is predicted in an online and offline basis. In the basis of offline predict, initially an error occurs, and if the sign matches the image learned by machine learning methods, then the gesture name is typed in the predict textbox, and the true sign is added to the XML database. If no match is found, then an error is keyed in instead of the sign name. This process is shown in Figure 5.12.

The accuracy and ability of K-NN, SVM and NB algorithms vary between %90 - %95, under the same conditions, namely Kinect camera use, the distance between the person and the camera, and a good ambient light. In this application, a USB camera can be used instead of Kinect camera, as well as different distance, and changes in the ambient light conditions. However, these changes affect the percentage of accuracy recognition of each method. Meaning that those problems negatively affected by the change of the optimal normal conditions. Table 5.1 shows the accuracy results of each method for four gestures that contain two symbols and two numbers signs of hand in the culture of Iraq.

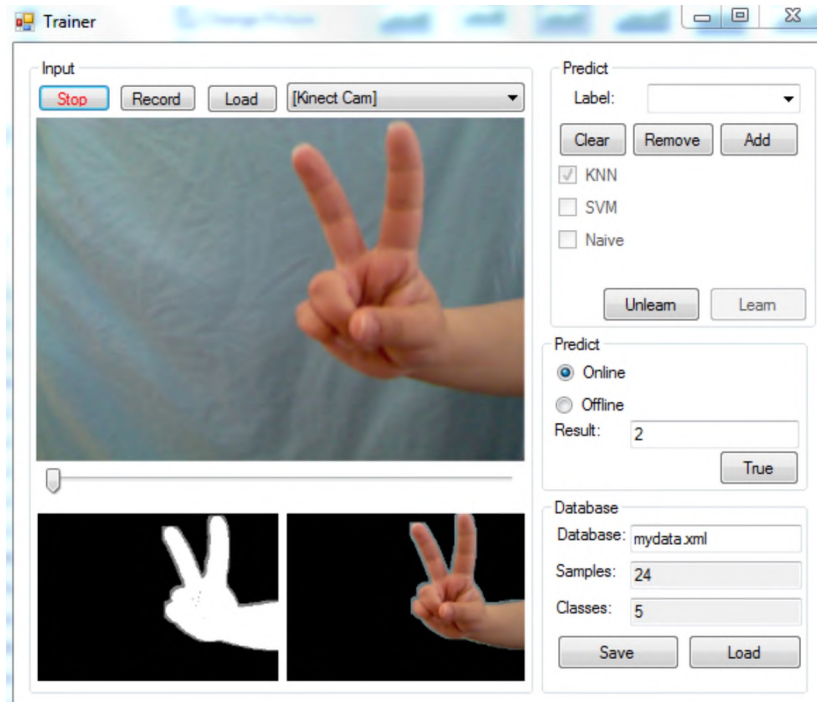


Figure 5.12 Hand recognition process

5.9. Results and Analysis

This thesis has presented the vision based automatic sign language recognition for Arabic symbols in the culture of Iraq. It strived to have a methodology that can assist in making an effective software for recognizing Arabic sign. This may also help all other cultures in the world to learn what is meant by Arabic hand signs and how the letters are created by hands in the Iraqi culture. If all the proposed features and methods of machine learning like SVM, K-NN, and NB are applied properly, the numeric and symbolic signs shown by the hand in the air using Kinect sensor can be recognized accurately for the specific hand gestures. Several hand gestures were properly classified with the concepts of the proposed software. The proposed application can be further developed to enable the communication between ordinary people and their special needs. In addition, a possible further implementation may include more signs from the Iraqi culture and/or other cultures.

Table 5.1. Accuracy rate of tested gesture

Methods	The Accuracy Percentage of the Tested Gestures			
	Gesture one	Gesture Two	Gesture Below	Gesture Respect
KNN	92%	90%	93%	90%
SVM	90%	92%	90%	93%
NB	90%	94%	92%	94%

In this research, one classification method can be applied and used, and based on it the training set can be tested as it can be seen from table 5.1. Also, there is an option for applying two methods together, for examples (K-NN and SVM) or (K-NN and Naïve Bayes) or (SVM and Naïve Bayes) to get the best and the most accurate results for hand gesture recognition. In order to classify the best accuracy, combined classification methods were tested and the results are provided in Table 5.2.

Table 5.2. The accuracy rate of using two methods together

Methods	The Accuracy Percentage of the Tested Gestures			
	Gesture one	Gesture Two	Gesture Below	Gesture Respect
KNN-SVM	96%	94%	97%	95%
SVM-NB	95%	94%	95%	93%
NB-KNN	97%	96%	97%	95%

Figure 5.13 illustrates, using a chart, the used classification methods' performance in order to distinguish the best result, especially when combined classifier are used. As it can be seen from Figure 5.13, a combination of Naïve Bayes classifier and k-Nearest Neighbor classifier are providing the highest accuracy results compared to all other methods, individual and combined.

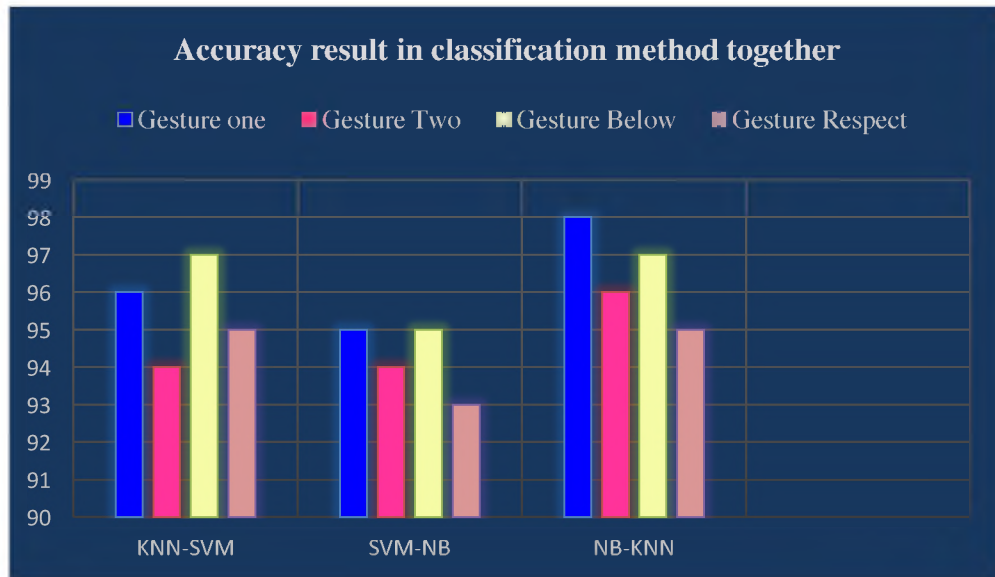


Figure 5.13 The accuracy of combined classification methods

6. CONCLUSION

In this thesis a detailed framework is presented for accurate real time Hand Gesture Recognition (HGR). The application of manipulating objects through hand gestures in virtual environment is being proposed and implemented in this thesis provides a suitable efficient and user friendly human computer interface. With the help of this application the user can interact with the virtual objects using hand gesture instead of any other physical input devices. The application provides the flexibility to the users and specifically physically challenged users to define the gesture according to their feasibility and ease of use. This thesis has presented the vision based automatic sign language recognition for Arabic symbols in the culture of Iraq. It strived to have a methodology that can assist in making an effective software for recognizing Arabic sign by using Machine Learning algorithms for classification like Support Vector Machine (SVM), k-Nearest Neighbors (k-NN) and Naïve Byes (NB). In this thesis we can put each of these three classification method one by one and achieve an accuracy rate and also can check or put two methods together to get better results. The Hand Gesture Recognition (HGR) may also help all other cultures in the world to learn the meaning of Arabic hand signs and HGR shows how the symbols are created by hands in the culture of Iraq, the purpose of this system is to translate sign language (Hand Gestures) into Text (Word) in Iraqi culture and other countries if you want because this system can recognize new symbols.

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Chia Fatah Aziz

Halabja, Kurdistan, Iraq
Email: chiafatah.cf@gmail.com
DOB: 1988

CAREER INTERETS

Teaching professional career that is imaginative and includes several artistic medium to encourage and inspire students by innovative and creative thoughts.

EDUCATION

- **B.Sc.**, (Computer Science) 2006-2010: from *Sulaimany University*, Kurdistan, Iraq
- **Higher School**, 2005-2006: from **Halabja High School for Girls** , Kurdistan, Iraq

EMPLOYMENT AND EXPERIENCE

- December 2010 – Present, , *ASSISTANT PROGRAMMER*, TECHNICAL COLLEGE OF APPLIED SCIENCES OF HALABJA / SULAIMANI POLYTECHNIC UNIVERSITY, KURDISTAN, IRAQ

COMPUTING SKILLLS

- Programming skills: C# .NET
- Operating Systems: Windows, Mac
- Applications: Photoshop, MS office
- Database: SQL Server
- Web Technologies: HTML, PHP

PROJECTS

B.Sc., Project Title – **Information Bank System**

PERSONAL DETAILS

Nationality: Iraqi
Known Languages: English, Arabic, Kurdish