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Rotation Invariant Technique for Sign Language Recognition

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ABSTRACT

Sign language recognition is an assistive technology that has garnered significant attention from researchers, particularly with respect to its potential benefits for individuals with hearing impairments. This paper proposes an effective technique for sign language recognition based on the Contourlet Transform (CT) and deep learning. The CT is employed in the pre-processing stage to reduce complexity and processing time, while deep learning is utilized to extract and classify sign language features. The proposed method was evaluated using two sign language databases: a direct feed database and an American sign language database. The experimental analysis demonstrated that the proposed method gives good results in processing time by more than 70% while maintaining high accuracy.

1. INTRODUCTION

Modern technology has the potential to make people's lives easier across all segments of society without any discrimination, which is one of its main advantages. People with special needs are a particularly important group that technology should aim to assist and enhance their efficiency. Sign language recognition (SLR) technology can significantly benefit individuals with hearing impairments. By recognizing hand movements, computers can interpret and convert them into understandable language through sound or writing [1]. Several types of SLR, like Sensor-based recognition, use various sensors, such as gloves or motion capture devices, to capture and analyze the movements and positions of the hands and other body parts during sign language production. [2] , Vision-based recognition that utilizes computer vision techniques to analyze video or image data of sign language gestures [3], Based on Hand Shape Recognition [4], Motion-based Recognition [5], Pose-based Recognition [6], 3D Depth-based Recognition [7] In this research, a proposed technique based on Vision recognition of Hand Shape was implemented to enhance the speed and accuracy of SLR. This was achieved by leveraging advanced artificial intelligence techniques, specifically CNN, and image processing technology called CT [8].

CT is a representation method designed explicitly for real two-dimensional images. It consists of two layers of filters: the Laplacian pyramid transform for multi-scale decomposition and a directional filter bank for multi-direction decomposition. This allows the CT to effectively capture essential features of the image through flexible multi-resolution and multi-direction decomposition. The research utilized two databases: the Direct Feed dataset, collected from a computer camera and pre-processed, and the American Sign Language (ASL) dataset. Extensive testing was conducted on these datasets, and the proposed approach demonstrated significant performance improvements compared to other contemporary techniques. Notably, the proposed technique achieved a remarkable 70% reduction in processing time while maintaining high accuracy. Overall, this

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research successfully employed CNN and CT to enhance the efficiency and effectiveness of SLR, showcasing promising results in speed and accuracy. The structure of this paper is organized as follows: Section 2 discusses CT in detail, followed by an explanation of CNN in Section 3. Section 4 provides an overview of the use of the OpenCV library. Section 5 describes the proposed method, while Section 6 presents the experiments conducted on the dataset. Finally, in Section 7, a comparison between the proposed technique and other existing methods is presented.

2. Related Works

Extensive scholarly endeavours have been devoted to identifying and interpreting manual gestures. However, there is a notable absence of research investigating possession time in conjunction with precision and rotation. , In 2018, Kumar et al. [9] proposed a research study, "A position and rotation invariant framework for sign language recognition (SLR) using Kinect."Talk about a resilient SLR (Sign Language Recognition) framework that is not affected by positional variations conducted extensive testing on a dataset comprising 2700 gestures. With the Hidden Markov Model (HMM) as methodology, the experimental outcomes demonstrate the effectiveness of our proposed framework, achieving an accuracy of 83.77% in recognizing occluded sign gestures. In a 2020 study by Wadhawan et al. [10], deep learning-based Convolutional Neural Networks (CNN) were utilized to create a robust model for recognizing static signs in sign language. The researchers collected 35,000 hand images from multiple users for 100 words in sign language. They achieved a high level of accuracy, with 99.72% and 99.90% accuracy on color and grayscale images, respectively, using precision, recall, and F-score measurements. In 2020, Barbhuiya et al. [11] proposed a study that employed deep learning-based CNNs to improve the robustness of modeling static signs in sign language recognition. They used modified pre-trained AlexNet and VGG16 architectures for feature extraction and a multiclass support vector machine (SVM) classifier. Their system achieved an impressive recognition accuracy of 99.82%, surpassing the performance of several state-of-the-art methods. In 2020, Saleh Aly and Walla Aly [12] proposed using deep learning architectures for signer-independent sign language recognition. Their approach incorporated hand-shape feature representation, hand semantic segmentation, and a deep recurrent neural network. To extract the shape and movement of the hand from input videos, they trained a method called deepArSLR using a dataset of images that included hand gestures. They utilized a Convolutional Self-Organizing Map (CSOM) layer to extract hand shape features. The dataset consisted of 23 isolated words from an Arabic sign language database captured by three users. The results demonstrated that their method outperformed other techniques in terms of recognition accuracy by a significant margin.

In 2021, Zaid et al. [13] Compare two methods for image recognition. CNN and SVM, or the classification of skin cancer and feature extraction, got 86,9% with SVM and 97. In 2021, Ikram et al. [14] aimed to make accurate predictions and analyze sign language symbols using deep learning methodologies. They developed an application that could recognize sign language and provide clear and precise results. Data collected from a webcam was used as input to train the model. It achieved 99.38% accuracy with excellent prediction and a small loss (0.0250). In 2021, K.Amrutha and P. Prabu [15] proposed an independent recognition model that utilized vision-based detection and recognition of isolated hand gestures. The model's performance was evaluated under controlled conditions, using four subjects, and a machine learning-based sign language recognition (SLR) model was employed. Feature extraction was carried out using a convex hull, and the K-Nearest Neighbor (KNN) algorithm was utilized for classification, achieving a 65% accuracy rate. In 2022, Akansha Tyagi and Sandhya Bansal [16] proposed a research study that addresses the problem of non-significant features in extracted elements that lead to increased processing time. The proposed solution utilizes an object detection system based on deep manual mathematics, employing a new approach called hand sign analysis. Positive results were obtained by reducing non-significant features and improving accuracy. Despite the numerous techniques used to identify sign language in previous research, they often focused solely on achieving high accuracy and did not adequately address the crucial aspect of time. In today's fast-paced world, time plays a vital role in the integration and usability of technology. Even if a program demonstrates high accuracy, its practical application and compatibility with modern technology may be hindered by differences in recognition time. Therefore, it is essential to consider accuracy and time to develop effective and practical Sign Language Recognition (SLR). Table 1 shows all related works' performance scale.

Table 1: shows all related works' performance scale

Ref	Year	Dataset type	Types of features extracted	Used of method	Performance scale
[9]	2018	Images	Hidden Markov Model (HMM)	Kinect	83.77%
[10]	2020	Images	CNN	CNN	99.72%
[11]	2020	Images	AlexNet & VGG16	CNN	99.82%
[12]	2020	Videos and Images	Convolutional Self-Organizing Map (CSOM)	deepArSLR	89.59%
[13]	2021	Images	SVM	CNN & SVM	86.9%
[14]	2021	Images	CNN	CNN	99.38%
[15]	2021	Images	convex hull	KNN	65 %
[16]	2022	Images	Handmark analysis of sign language (HMASL)	HMASL	87 %

3. The Contourlet Transform (CT)

CT is a two-dimensional transform designed for efficient and effective image processing[17]. The primary objective of this transformation was to preserve the inherent geometrical structure, which plays a crucial role in visual information. Unlike other transforms, the CT operates in the discrete domain and combines the curvelet and wavelet transforms in a multi-scale approach. This integration enables the CT to effectively retain geometric information within images, including contours and edges. By preserving such key features, the transform proves valuable in various image processing applications, such as compression, feature extraction, and denoising. The CT offers a compact representation of the image while maintaining its quality, as it selectively discards less significant information. To illustrate the concept, Fig 1 provides a conceptual depiction of the CT [18]. Overall, the CT introduced has proven to be a powerful tool in image processing, leveraging a discrete multi-scale approach that integrates curvelet and wavelet transforms. Its ability to preserve geometric details has made it valuable in applications like compression[19], feature extraction[20], and denoising[21].

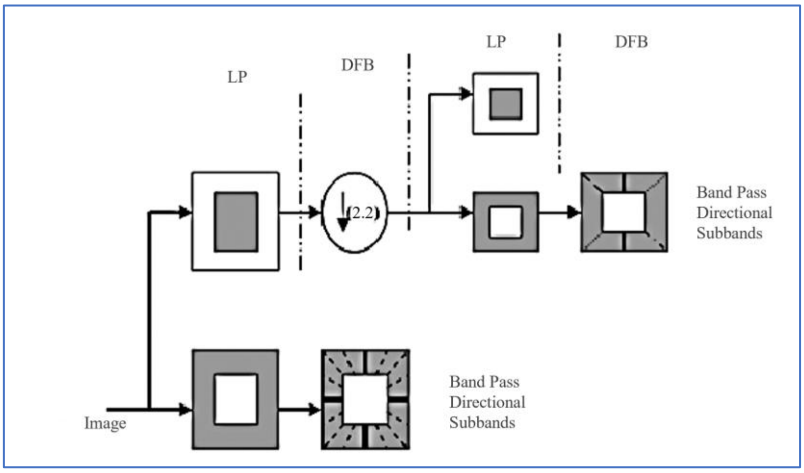

Figure 1: Display of a conceptual drawing of CT [18].

It comprises two primary components: the curvelet transform and the wavelet transform. The wavelet transform [22] decomposes the image into different frequency subbands, while the curvelet transform[23] preserves the directional information present in the image. The mathematical representation of the CT involves multiple steps. These steps include the decomposition of the image using a wavelet transform, directional decomposition using a curvelet transform, encoding of the image data using coefficients in the wavelet and curvelet domains, and reconstruction of the image from the encoded coefficients. as shown in Fig 2 some example of CT

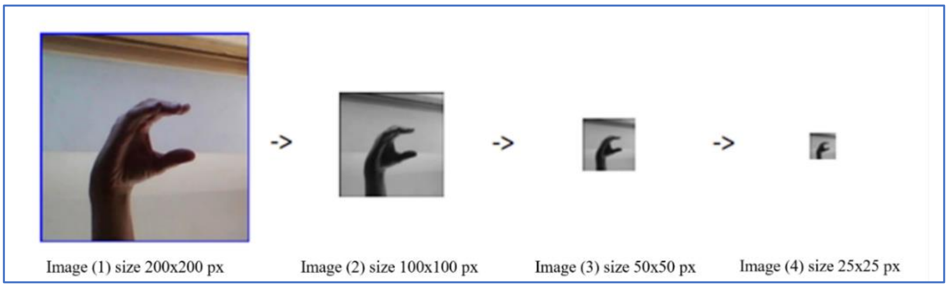

Figure 2: Contourlet Transform Image Levels.

4. Convolutional Neural Networks (CNN)

A CNN is an artificial neural network primarily utilized for image recognition and classification tasks [24]. It's called "convolutional" because it employs convolution, a mathematical operation, to extract features from input images. In the context of SLR, CNNs can analyze sequences of images (i.e., video frames) and classify them into different classes (e.g., different signs). The network can learn to recognize patterns in the images, such as hand shapes and motion, relevant to the sign being performed and use this information to make predictions. This makes CNNs a powerful tool for SLR as they can automatically learn to recognize signs from training data instead of relying on manual feature engineering. The layers of a CNN can be categorized into four layers see Fig 3,4: Convolutional layer: The convolutional layer applies a convolution operation to the input data, helping the network learn local features in the image.

- Activation Layer: The activation layer applies a non-linear activation function (such as ReLU, sigmoid, or tanh) element-wise to the feature maps obtained from the convolutional layer. It introduces non-linearity into the network, allowing it to learn complex relationships and make it more expressive.

- Pooling layer: The pooling layer down samples the feature map produced by the convolutional layer, which reduces the dimensionality of the data and makes the network more invariant to small translations in the input

- Fully connected layer: The fully connected layer is a traditional neural network layer that employs all the features learned by the previous layers to make the final prediction.

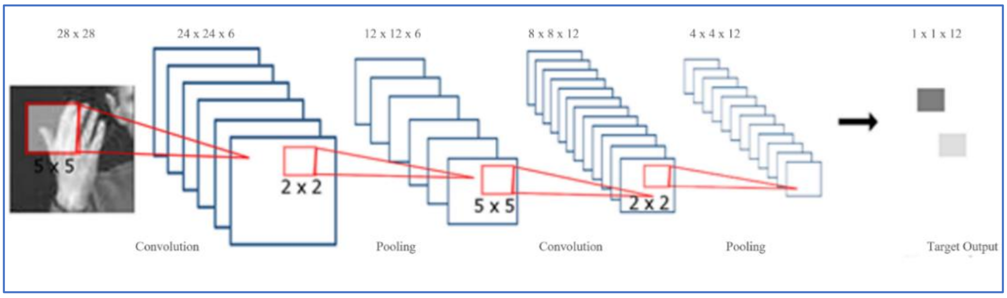

Figure 3: Architecture of CNN to train the hands model [25].

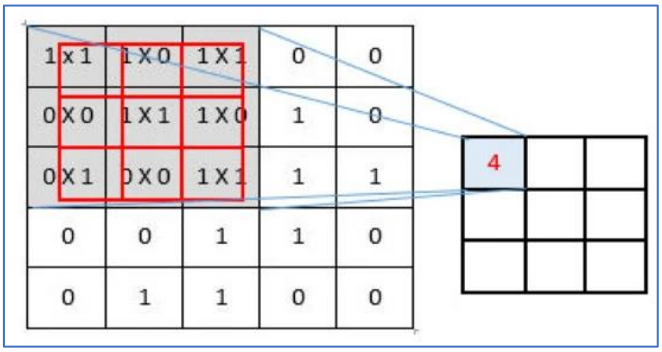

Figure 4: First step of convolution [26].

4. The proposed method

The current study introduces a method for SLR using CNN. CT, the proposed approach incorporates two databases, namely a real-time feed from a computer camera and the ASL database. The method consists of four key stages, as illustrated in Fig 5:Collection of databases: The process of preparing databases will start with obtaining an official database from the Internet and, in addition, a database obtained from a direct feed of the computer camera will be created by capturing the visible hand movement within the Region of Interest (ROI) and dividing it into two files, "train" and "test", each containing ten classes, with the possibility of increasing the number of classes as needed. Application of the CT Decomposition: This step involves applying the CT algorithm to the database to obtain images that contain fewer and more important features while reducing their size.

Training using CNN: In this stage, the processed dataset will be used to train the CNN, which will involve several important steps, including the Convolutional layer, Pooling layer, Activation layer, Fully Connected layer, and Output layer. The Convolutional layer performs the convolution operation on the input data to detect features and reduce their dimensionality. The Pooling layer performs down-sampling on the feature maps to reduce their size and retain the most important information. The Activation layer applies activation functions such as ReLU to introduce non-linearity into the model, the Fully Connected layer connects every neuron in one layer to every neuron in another layer, enabling high-level reasoning for classification, and the Output layer is used for classification, returning the predicted class label based on the inputs. Development of a trained model: The final stage is to produce a trained model that can accurately and quickly recognize sign language from an online camera feed efficiently and effectively.

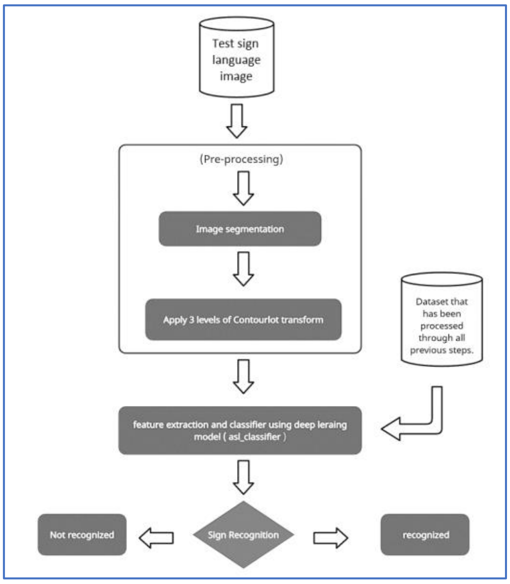

Figure 5: Block diagram of the suggested technique.

6. Experimental analysis

The study aimed to assess the efficiency of the proposed approach in improving the accuracy and speed of SLR systems by testing multiple databases. These databases comprised a self-made database captured through a computer camera, the ASL database, to compress images. The CT technique was utilized to retain significant features while reducing image size. The experimental part is performed in Visual Studio Code using processor: AND Ryzen 5 5600G with Radeon Graphics C.P.U 3.90 GHz and 16.0 GB RAM.

6.1 Direct feed Dataset

The proposed database was created by capturing video feeds using a computer camera. The area where the hand gesture was present was identified as the Region of Interest (ROI). Segmentation was performed using the OpenCV library to extract the hand gesture from each frame. The resulting dataset comprised ten classes, each containing 701 images. The background of the images was estimated by calculating the accumulated weighted average and subtracting it from frames containing foreground objects that were distinguishable from the background. The images were saved as jpg files with 200 x 200 pixels[27]. Some sample images from the dataset can be seen in Fig 6.

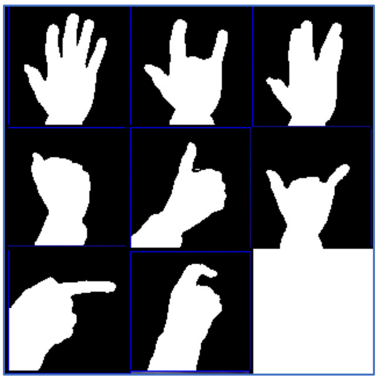

Figure 6: Images from the dataset

6.2 American Sign Language Dataset (ASL DS)

The database comprises a comprehensive collection of 87,000 hand alphabet images categorized into 29 classes. These classes represent the 26 letters of the alphabet (A-Z), along with three additional classes representing “space,” “delete,” and “NOTHING.” Each class includes 3,000 images for training, while 600 images per class are reserved for testing purposes. The size of each image in this database is 200 x 200 pixels [28]. Fig 7 displays some sample images from the dataset.

Figure 7: -Images from the ASL dataset

6.3 Accuracy and Time of Direct Feed Dataset

Two experiments were conducted to evaluate the accuracy and speed of the proposed approach. In the first experiment, 300 images from each class 10 images were randomly selected, with 80% (240) images used for training and 20% (60) for testing in each class. In the second experiment, 200 images from 10 classes used 80% (170) images for training and 20% (35) images for testing, with a random splitting technique used to partition the data into training and testing sets. Various transformations, including shear and zoom, were applied to the data. The results of the experiments are presented in Table 2 and Fig 8. CT employed in this study comprises three levels that progressively reduce the size of the images. In this database, where the original image size is 200 x 200 pixels, the first-level resize is neglected due to a significant drop in accuracy. The researcher observed that, at the third level, the accuracy of both the training and validation sets was maintained. At the same time, the transformation time was significantly reduced compared to the other levels. Therefore, the third level was chosen, as shown in Table 3.

The efficacy of using a Contourlet transform-based CNN versus a CNN alone for sign language image classification was evaluated using both the first and second datasets. The results showed that the Contourlet transform-based CNN outperformed both the CNN alone and other accuracy and time efficiency methods. The improved performance of the Contourlet transform-based CNN is attributed to its ability to capture intrinsic directional information and geometric features of the sign language images, which are better preserved and enhanced by the Contourlet transform. Additionally, using the CT helped reduce the dimensionality of the input data, leading to improved efficiency in processing time.

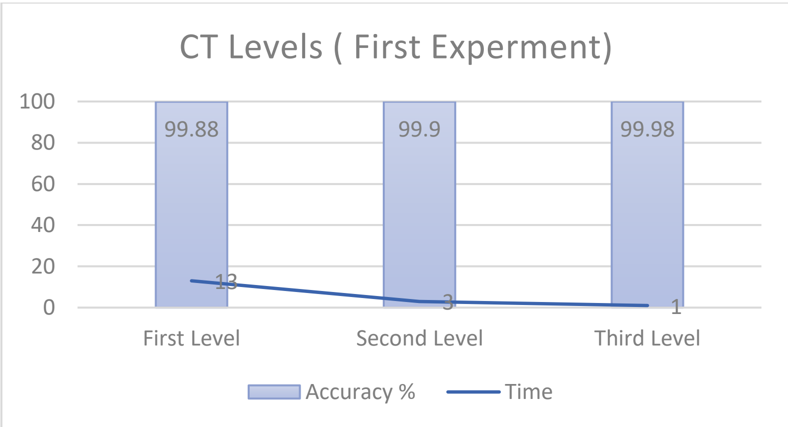

Figure 8: - Contourlet Transform-based CNN with Different Levels on direct feed dataset.

Table 2: Contourlet Transform-based CNN with Different Levels on Direct feed dataset.

CT Levels	**CNN**		**CNN Based-Contourlet Transform**	
	Accuracy (%)	Time	Accuracy (%)	Time
First Level	99.88	13	99.85	9
Second Level	99.90	3	99.89	2
Third Level	99.98	1	99.99	1

Table 3: Result of the Experiments on the direct feed dataset.

CT Levels	**First Experiment**		**Second Experiment**	
	Accuracy (%)	Time	Accuracy (%)	Time
First Experiment	99.10	53	99.98	1
Second Experiment	99.56	28	99.99	1

6.4 Accuracy and Time of American Sign Language Dataset

Two experiments were conducted to evaluate and compare the efficacy of a particular approach. The first experiment involved selecting random images from a pool of 2000 images in each of the 10 available classes.80% (1600) of images were used for training, while 20% (400) were reserved for testing in each class. In the second experiment, a pool of 1000 images was used for each of the ten available classes. 80% (800) images were employed for training, while 20% (200) were selected for testing. We partitioned the data into training and testing sets using a random splitting technique. Additionally, we applied various transformations to the data, including shear and zoom, Table 4, Fig 9.
The CT is composed of three levels, with each level progressively reducing the size of the images. In our specific database, where the original image size is 200 x 200, the first level resizes the image to 100 x 100, the second level to 50 x 50, and the third level to 25 x 25. The fourth level is neglected due to a significant drop in accuracy. The researcher observed that, in the third level, the accuracy of both the training and validation sets is maintained. At the same time, the transformation time is significantly reduced compared to the other levels. Therefore, the third level is chosen for this reason. Table 5. presented the accuracy and time results of the experiment mentioned above. We experimented using the first and second datasets on the efficacy of using a Contourlet transform-based CNN, a CNN alone, for sign language image classification. Our findings demonstrated that the Contourlet transform-based CNN outperformed the CNN alone and other accuracy and time efficiency methods. This improved performance is due to CT's ability to capture the sign language images' intrinsic directional information and geometric features. This information is better preserved and enhanced by the Contourlet transform. Furthermore, using the CT also helped reduce the dimensionality of the input data, leading to improved efficiency in processing time.

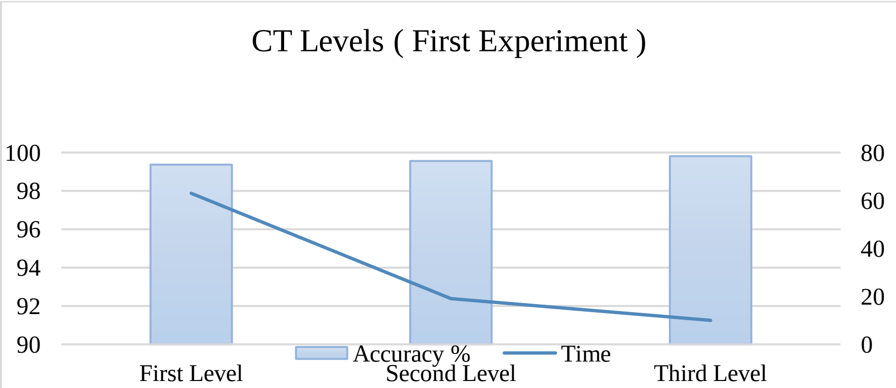

Figure 9: Contourlet Transform-based CNN with Different Levels on direct feed dataset.

Table 4: Results of Applying Three Levels of CT over ASL Dataset in both First and Second Experiment

CT Levels	First Experiment		Second Experiment	
	Accuracy (%)	Time	Accuracy (%)	Time
First Level	99.37	63	99.40	30
Second Level	99.56	19	99.74	9
Third Level	99.81	10	99.96	4

Table 5: Result of the Experiments on direct feed dataset.

CT Levels	CNN		CNN Based-Contourlet Transform	
	Accuracy (%)	Time	Accuracy (%)	Time
First Experiment	98.80	281	99.96	10
Second Experiment	99.07	141	99.81	4

6.5 The evaluation of the proposed approach against the Rotation

Rotation is a challenge faced by most SLR programs, as it can distort images and cause interference with the hands in the image. However, if the correct techniques are used, rotation can significantly improve the accuracy of the SLR system, which is consistent with the results of recent scientific studies. A pool of 2000 images in each of the ten available classes.80% (1600) images were used for training, while 20% (400) The researcher added rotation to the tested database, and a significant improvement in the accuracy of the SLR system was observed after adding rotation. Fig 10 some samples of the dataset

Table 6. Fig 11 shows that rotations were randomly added to the test part of the proposed database at different ratios, including 90 and 180 degrees, and the results showed high accuracy in image recognition. This indicates the system's ability to deal with the challenges associated with rotation and the effectiveness of using the correct techniques in the field of SLR.

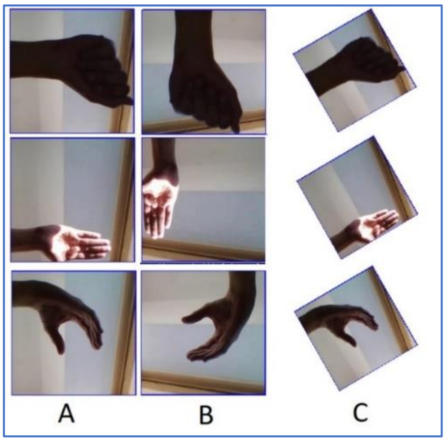

Figure 10: some dataset samples with Rotation (A: right 90, B: 180, C: 60).

Table 6: Result of the Experiments on the direct feed dataset.

CT Levels	CNN		CNN Based-Contourlet Transform	
	Accuracy (%)	Time	Accuracy (%)	Time
Rotation Range 90	92.40	311	97.35	4
Rotation Range 180	92.12	311	97.10	4
Rotation Range 60	93.89	311	98.89	4

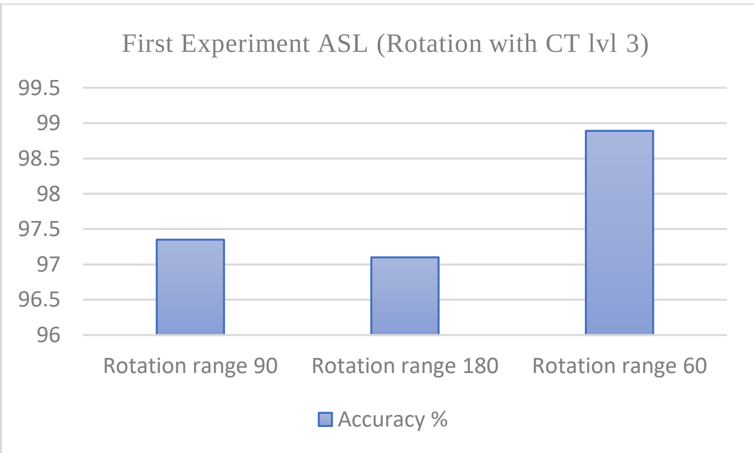

Figure 11: Rotation test result with ASL dataset

7. CONCLUSION

In the proposed approach, the researcher focused on one of the important aspects at this time, which had not been addressed previously in the research, which is the aspect of speed in the context of SLR. Previous research has primarily focused on increasing the accuracy of SLR systems while ignoring the aspect of speed. However, the proposed method outperforms performance in terms of speed, with a significant increase of over 70% in processing speed, as verified through experiments on both self-created and official databases of ASL. The proposed method showed its superiority in terms of speed, so it was able to increase the processing speed to more than 70%.

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9. CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this paper.

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