**Title Page:**

Improving Accessibility: Boosting Precision in Translating Text to Sign Language by Comparing DTW and HMMs

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**Keywords:** Text-to-Sign, Dumb and Deaf, Dynamic Time Warping (DTW), Hidden Markov Models (HMMs), Speech-Impaired.

**Abstract**

**Aim:** Ensuring equal opportunity for all individuals, including those in the Dumb and Deaf community, is a fundamental human right. Access to information is crucial, and to facilitate communication between Dumb and Deaf individuals, there is a need for a direct, automated mode of communication. This paper presents a comprehensive survey of both traditional and cutting-edge projects in sign language machine translation and Text-to-Sign language generation. Furthermore, the Dynamic Time Warping (DTW), and Hidden Markov Models (HMMs) algorithms optimize the translation process between text and sign language. This integration aims to reduce dependence on human interpreters and foster a more inclusive and accessible environment for the Dumb and Deaf society. **Materials and Methods:** The total samples of 7173 have been split into two different groups. Methodologically, 80 % of his dataset, totaling 5738 samples, was dedicated to training these predictive models. The remaining 20 %, consisting of 1435 samples, was allocated for meticulous testing and validation. Rigorous adherence to a statistical power of 85 %, α = 0.05, and N = 20 iterations was calculated using clincalc.com. The research work meticulously employed two distinct methodologies: Group 1 entailed a DTW algorithm, while Group 2 adeptly utilized the HMMs algorithm. The efficacy of these models in presaging potential Text-to-Sign language. **Result** : With an accuracy of 83.83 %, HMMs model outperformed DTW with a 73.31 % accuracy. According to the independent sample t-test, the performance difference was statistically significant (p = 0.04, p < 0.05). The achieved significance value is 0.004 which shows that there is statistical significance between the two algorithms considered for the Text-to-Sign. Various approaches Text-to-Sign are discussed in this paper and compared with the existing models. **Conclusion** : The performance of the HMMs algorithm significantly outperforms that of the DTW algorithm, showcasing notably enhanced accuracy.

**Keywords:** Text-to-Sign, Dumb and Deaf, Dynamic Time Warping (DTW), Hidden Markov Models (HMMs), Basic Literacy Skills.

# **INTRODUCTION**

Over the course of human history, effective communication has played a pivotal role in shaping the evolution of our species. In contemporary society, the intricacies of day-to-day activities and businesses necessitate a common language understood by all parties involved in sign language [(Kahlon and Singh 2021)](https://paperpile.com/c/16YQp0/r6SK). The 2011 census in India revealed that 63 million people suffer from significant hearing disabilities, comprising 6.3% of the population. Shockingly, 76-89% of them lack knowledge of Indian Sign Language (ISL), primarily due to the scarcity of interpreters, inadequate ISL resources, and limited research [(Sonawane et al. 2021)](https://paperpile.com/c/16YQp0/jrY7). The ISLRTC (Indian Sign Language Research & Training Center) seeks to balance the principles of program and application of ISL. A widespread practice for Dumb and Deaf people in India is to learn ASL since it is very easily readable and then later learn sign language [(Monga et al. 2021)](https://paperpile.com/c/16YQp0/G4Kc). The purpose of the study is to provide a literature review of the work done on sign language (SL) around the world and in Pakistan and to develop a translation tool of Speech-Impaired and text to Pakistan Sign Language (PSL) with bilingual subtitles. Information and communication technology and tools development for teaching and learning purposes improve the learning process and facilitate both teachers and students [(Abbas and Sarfraz 2018)](https://paperpile.com/c/16YQp0/uwE4).

A collection of around 200 articles from platforms like Google Scholar, IEEE Xplore, and Springer has been amassed over the past 5 years. Text-to-Sign language recognition using Hilbert curve features. In: International conference image analysis and recognition. Springer, Berlin, Heidelberg, pp 143–151 [(Ragab, Ahmed, and Chau 2013)](https://paperpile.com/c/16YQp0/AKIs). In an experiment utilizing six hand signals from American Sign Language (ASL), findings revealed a recognition accuracy exceeding 90%. For intricate movements, a rotating plaster model was assessed with a 10-degree increment. The mean recognition accuracy also surpassed 90% [(Kim et al. 2017)](https://paperpile.com/c/16YQp0/sRIW). Through offline experimentation, this study endeavors to investigate a specific facet: the potential for linguistic interaction with paralyzed patients solely through neural brain activity. Electroencephalogram (EEG) readings were collected while participants mentally simulated the performance of six one-handed ASL signs [(AlQattan and Sepulveda 2017)](https://paperpile.com/c/16YQp0/A9x2).

The research gap for Text-to-Sign language recognition from the dataset from a long distance and sometimes, there is false prediction in Text-to-Sign in the datasets. The existing methods are found to have less accuracy in recognizing the Text-to-Sign Language and take a considerable amount of time in alerting the Dumb and Deaf. The main objective of the research is to get better accuracy by comparing two algorithms:Feedforward Dynamic Time Warping (DTW) and Hidden Markov Models (HMMs) for Text-to-Sign.

# **MATERIALS AND METHODS**

This research was conducted in the ideation laboratory, Saveetha School of Engineering at Saveetha Institute of Medical And Technical Sciences (SIMATS) in Chennai, India using Jupyter software[(Toomey 2018)](https://paperpile.com/c/16YQp0/WK4E9). The open-access Kaggle dataset served as the dataset for the research. The sample size for the comparison of two algorithms was determined for N = 20 iterations, power = 85 %, α = 0.05 using clincalc.com A total of 7173 sample sign language were given for training and 5738 sample profiles for training and comparison. 80 % of the dataset is utilized for training, while the remaining 20 % is used for testing and validation.Text-to-Sign language serves as the fundamental mode of communication within the hearing-impaired community, employing hand gestures, body language, and facial expressions. To enhance communication between Dumb and Deaf individuals and the wider society, techniques for recognizing hand gestures are employed to create Sign Language Recognition (SLR) systems, enabling the translation of Text-to-Sign language into spoken words or written text [(Azar and Seyedarabi 2016)](https://paperpile.com/c/16YQp0/aVqs).

To run the framework for the research requires 4GB of RAM space which will help in faster processing of the programs. In terms of processor, Intel(R) CPU @ 1.10GHz was used and any above version is recommended. As for Operating Systems, Windows 11 is used.

A storage space of 30GB is required in the system to store all the necessary images of the dataset that are collected and downloaded from the internet, store code, and install necessary plugins to help the code. Jupyter Notebook is used to run the framework and to test the program with images having speed bumps in them.

**DTW**

The DTW algorithm proves useful for aligning and matching text sequences with visual representations. This task is essential for generating accurate and contextually relevant images based on textual input. The research involves creating a system that converts textual descriptions of scenes or objects from Speech-Impaired into images. The goal is to ensure that the generated images closely align with the semantics and details described in the text. The DTW algorithm, known for its effectiveness in aligning sequences, can be employed to match the textural descriptions with a database of visual features or templates. By incorporating the DTW algorithm into the text-to-image conversion process, the research paper can showcase a robust and adaptive system capable of accurately translating textual descriptions into visually coherent images, catering to a wide range of input scenarios [(Lu, Amino, and Jing 2023)](https://paperpile.com/c/16YQp0/kfF7).

Dynamic Time Warping (DTW) algorithm steps:

| Step 1: | Preprocessing images containing sign language gestures to enhance features and reduce noise.Optionally, resize or normalize the images to a standard size for consistency. |
| --- | --- |
| Step 2: | Feature extraction techniques such as Histogram of Oriented Gradients (HOG) to extract relevant features from the preprocessed images.  images. |
| Step 3: | Dataset Preparation divides the dataset into training and testing sets and ensures a balanced distribution of different sign language gestures across the sets. |
| Step 4: | Dynamic Time Warping each pair of test image and training image computes the similarity/distance between the feature vectors of the test image and the training image to find the optimal alignment between the feature sequences of the two images. |
| Step 5: | Classification of DTW distances/similarities obtained in the previous step as input to a classification algorithm, such as Hidden Markov Models (HMMs). Predict the sign language gesture of the test images using the trained HMMs classifier. |
| Step 6: | Evaluation the performance of the sign language recognition system using metrics such as accuracy, precision, recall, and F1-score. Optionally, fine-tune parameters or explore different feature extraction techniques to improve performance. |

| Step 7: | Optimization and Deployment model for efficiency and speed, if necessary.  Deploy the trained model for real-time sign language recognition applications, ensuring compatibility with the target platform. |
| --- | --- |

**HMMS**

To convert textual descriptions into corresponding images using Hidden Markov Models. In this scenario, HMMs can be leveraged to model the temporal dependencies and transitions between different states, facilitating a more nuanced and context-aware mapping from text to images.The goal is to create a system that not only considers the semantic content of the text but also captures the temporal evolution of scenes or objects described in the text. HMMs, with their ability to model sequential data and transitions between states, can be employed to encode the temporal structure inherent in textual descriptions and their visual counterpart. Incorporating Hidden Markov Models into the text-to-image conversion process enhances the research paper by introducing a mechanism to capture temporal dependencies and transitions, leading to a more sophisticated and context-aware generation of images from textual descriptions [(Rabiner 1989)](https://paperpile.com/c/16YQp0/OEnq).

Hidden Markov Models (HMMs) algorithm steps:

| Step 1: | Capture Signs Gather images of Text-to-Sign language gestures. Enhance features and reduce noise. |
| --- | --- |
| Step 2: | Feature Magic features using techniques like HOG.These features are like secret spells that reveal the essence of each gesture. |
| Step 3: | Time Warp Quest embarks on a quest with Dynamic Time Warping (DTW). Calculate the mystical similarity between test and training features.Align the time sequences for optimal magic. |
| Step 4: | HMM IncantationsInvoke the power of Hidden Markov Models. Train them using the DTW distances. Predict gestures like a sorcerer divining the future in terms of Speech-Impaired. |
| Step 5: | Oracle’s Judgment Evaluate the magic’s accuracy, precision, and recall. Tweak parameters or try new spells for better results. |
| Step 6: | Optimize the Spellbook Sharpen the model for speed and efficiency. Deploy it for real-time Text-to-Sign language magic. |

# **Statistical Analysis**

The proposed HMMs algorithms are statistically evaluated using SPSS (Statistical Product and Service Solutions) version 27.0.1[(McCormick and Salcedo 2017)](https://paperpile.com/c/16YQp0/3O1MT). The two groups are assessed in this research using an independent sample T-test. The dependent variable is accuracy, while the input dataset and epoch time are independent variables.

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# **RESULTS**

The primary objective of this research was to evaluate the effectiveness of newly proposed Dumb and Deaf for HMMs in comparison to the DTW algorithm. The results clearly demonstrated a significant superiority of the HMMs approach over the DTW algorithm, particularly in terms of accuracy. Employing statistical analysis through the SPSS tool, the performance of these two algorithms underwent thorough comparison and scrutiny.

The dataset utilized for this analysis included columns such as images, alphabets. A subset of 20 samples was extracted from a larger dataset comprising 7172 profiles. The accuracy of both DTW and HMMs for each iteration is presented in Table 2. Comparative analysis of the algorithms revealed that the HMMs consistently achieved a higher mean accuracy of 83.83%, outperforming the DTW model with a mean accuracy of 73.31%, as illustrated in Table 3.

Furthermore, the results highlighted that the HMMs model maintained a higher mean accuracy value compared to the DTW model, with respective standard deviations of 7.581 and 14.308. The statistical significance of these findings was confirmed by the Independent Sample T-test, both algorithms exhibiting a significant p-value of 0.04 (p < 0.05 for independent sample t-test), as indicated in Table 4. These outcomes collectively underscore the robust performance of the HMMs in this comparative analysis[(Zhang, Zhou, and Li 2014)](https://paperpile.com/c/16YQp0/ii8V).

# **DISCUSSION**

The research results show that the HMMs is significantly more accurate than the DTW and the significance value of p = 0.04 (p < 0.05 independent sample t-test ). The HMMs had an accuracy of 83.83 % , while the DTW had an accuracy of 73.31 %.

Hidden Markov Models (HMMs), which are commonly used for Speech-Impaired and gesture recognition, asynchrony refers to the possibility that different streams (such as audio and visual) may not align perfectly. Instead of moving in lockstep, they exhibit variations in timing or state transitions [(Theodorakis, Katsamanis, and Maragos 2009)](https://paperpile.com/c/16YQp0/jEtB). The data glove merges bending and inertial sensors to capture intricate hand movements, pivotal for sign language recognition. Its weighted DTW fusion technique enhances accuracy by adjusting for varying gestures. This innovation promises precise real-time recognition, adaptability to individual styles, user-friendly wearability, and portability, marking a significant leap in inclusive communication for the hearing impaired [(Lu, Amino, and Jing 2023)](https://paperpile.com/c/16YQp0/kfF7).This examination further explores the historical and cultural aspects of Text-to-Sign languages, offering insights into how these languages have evolved over time and the ways in which Dumb and Deaf culture has shaped their growth [(Gunjal and Dept.ofComputer Engineering SKN Sinhgad Institute of Technology & Science, Lonavala, Maharashtra 2024)](https://paperpile.com/c/16YQp0/2V6P).

Sign generation, a critical component of sign language machine translation, is undergoing scrutiny for its naturalness, particularly in the context of 3D avatars [(Shovkovy et al. 2023)](https://paperpile.com/c/16YQp0/vgi9). Current studies highlight the suitability of avatar animation but acknowledge challenges in achieving widespread acceptance within the Dumb and Deaf community. Future investigations may concentrate on temporal coordination between manual and non-manual components, enhancing the natural appearance of signing. Alternatively, exploring methods beyond 3D avatars, Speech-Impaired, such as synthesizing detailed sign videos, presents a pragmatic avenue for advancing sign generation capabilities. The intricate features of sign language data, including motion size and speed, should be a focal point for refinement in data processing strategies. In essence, these avenues collectively pave the way for a more accurate, inclusive, and natural machine translation of sign language, contributing to improved communication for the Dumb and Deaf community.

# **CONCLUSION**

The research work aimed to enhance Sign Language using both a DTW approach and HMMs. The HMMs model attained an accuracy of 83.83 %, while the DTW achieved 73.31 %. These results showed a significant superiority of the HMMs over the DTW in improving sign language. The superiority of HMMs can be attributed to their ability to capture complex temporal dependencies and variability inherent in sign gestures, as well as their robustness to variations in execution speed, duration, and style. Additionally, HMMs offer scalability and adaptability, making them suitable for accommodating a larger vocabulary of signs and different singing styles. These findings have significant implications for the field of assistive technology and communication accessibility for individuals with hearing impairments. By leveraging advanced machine learning techniques like HMMs, Sign Language recognition systems can be developed to provide more accurate and reliable communication support, ultimately enhancing the quality of life for those who rely on Sign Language for communication. Further research in this area could explore additional improvements and optimizations to continue advancing Sign Language recognition technology.

**DECLARATIONS**

**Conflicts of Interests**

No conflict of interest in this manuscript.

# **Authors Contribution**

Author MKS was involved in data collection, data analysis, and manuscript writing. Author WDP was involved in conceptualization, data validation, and critical reviews of manuscripts.

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# **REFERENCES**

[Abbas, Ali, and Summaira Sarfraz. 2018. “Developing a Prototype to Translate Text and Speech to Pakistan Sign Language with Bilingual Subtitles: A Framework.” *Journal of Educational Technology Systems* 47 (2): 248–66.](http://paperpile.com/b/16YQp0/uwE4)

[AlQattan, Duaa, and Francisco Sepulveda. 2017. “Towards Sign Language Recognition Using EEG-Based Motor Imagery Brain Computer Interface.” In *2017 5th International Winter Conference on Brain-Computer Interface (BCI)*. IEEE. https://doi.org/](http://paperpile.com/b/16YQp0/A9x2)[10.1109/iww-bci.2017.7858143](http://dx.doi.org/10.1109/iww-bci.2017.7858143)[.](http://paperpile.com/b/16YQp0/A9x2)

[Azar, Saeideh Ghanbari, and Hadi Seyedarabi. 2016. “Continuous Hidden Markov Model Based Dynamic Persian Sign Language Recognition.” In *2016 24th Iranian Conference on Electrical Engineering (ICEE)*. IEEE. https://doi.org/](http://paperpile.com/b/16YQp0/aVqs)[10.1109/iraniancee.2016.7585687](http://dx.doi.org/10.1109/iraniancee.2016.7585687)[.](http://paperpile.com/b/16YQp0/aVqs)

[Gunjal, Prof S. P., and Dept.ofComputer Engineering SKN Sinhgad Institute of Technology & Science, Lonavala, Maharashtra. 2024. “Sign Language Analysis Using CNN Algorithm.” *INTERNATIONAL JOURNAL OF SCIENTIFIC RESEARCH IN ENGINEERING AND MANAGEMENT* 08 (01): 1–6.](http://paperpile.com/b/16YQp0/2V6P)

[Kahlon, Navroz Kaur, and Williamjeet Singh. 2021. “Machine Translation from Text to Sign Language: A Systematic Review.” *Universal Access in the Information Society*, July. https://doi.org/](http://paperpile.com/b/16YQp0/r6SK)[10.1007/s10209-021-00823-1](http://dx.doi.org/10.1007/s10209-021-00823-1)[.](http://paperpile.com/b/16YQp0/r6SK)

[Kim, Seo Yul, Hong Gul Han, Jin Woo Kim, Sanghoon Lee, and Tae Wook Kim. 2017. “A Hand Gesture Recognition Sensor Using Reflected Impulses.” *IEEE Sensors Journal* 17 (10): 2975–76.](http://paperpile.com/b/16YQp0/sRIW)

[Lu, Chenghong, Shingo Amino, and Lei Jing. 2023. “Data Glove with Bending Sensor and Inertial Sensor Based on Weighted DTW Fusion for Sign Language Recognition.” *Electronics* 12 (3): 613.](http://paperpile.com/b/16YQp0/kfF7)

[McCormick, Keith, and Jesus Salcedo. 2017. *SPSS Statistics for Data Analysis and Visualization*. John Wiley & Sons.](http://paperpile.com/b/16YQp0/3O1MT)

[Monga, Hemang, Jatin Bhutani, Muskan Ahuja, Nikita Maid, and Himangi Pande. 2021. “Speech to Indian Sign Language Translator.” In *Recent Trends in Intensive Computing*. Advances in Parallel Computing. IOS Press.](http://paperpile.com/b/16YQp0/G4Kc)

[Rabiner, L. R. 1989. “A Tutorial on Hidden Markov Models and Selected Applications in Speech Recognition.” *Proceedings of the IEEE. Institute of Electrical and Electronics Engineers* 77 (2): 257–86.](http://paperpile.com/b/16YQp0/OEnq)

[Ragab, Amira, Maher Ahmed, and Siu-Cheung Chau. 2013. “Sign Language Recognition Using Hilbert Curve Features.” In *Lecture Notes in Computer Science*, 143–51. Lecture Notes in Computer Science. Berlin, Heidelberg: Springer Berlin Heidelberg.](http://paperpile.com/b/16YQp0/AKIs)

[Shovkovy, Yevhenii, Olena Grynyova, Serhii Udovenko, and Larysa Chala. 2023. “Automatic Sign Language Translation System Using Neural Network Technologies and 3D Animation.” *Innovative Technologies and Scientific Solutions for Industries*, no. 4(26) (December): 108–21.](http://paperpile.com/b/16YQp0/vgi9)

[Sonawane, Pankaj, Karan Shah, Parth Patel, Shikhar Shah, and Jay Shah. 2021. “Speech to Indian Sign Language (ISL) Translation System.” In *2021 International Conference on Computing, Communication, and Intelligent Systems (ICCIS)*. IEEE. https://doi.org/](http://paperpile.com/b/16YQp0/jrY7)[10.1109/icccis51004.2021.9397097](http://dx.doi.org/10.1109/icccis51004.2021.9397097)[.](http://paperpile.com/b/16YQp0/jrY7)

[Theodorakis, Stavros, Athanassios Katsamanis, and Petros Maragos. 2009. “Product-HMMs for Automatic Sign Language Recognition.” In *2009 IEEE International Conference on Acoustics, Speech and Signal Processing*. IEEE. https://doi.org/](http://paperpile.com/b/16YQp0/jEtB)[10.1109/icassp.2009.4959905](http://dx.doi.org/10.1109/icassp.2009.4959905)[.](http://paperpile.com/b/16YQp0/jEtB)

[Toomey, Dan. 2018. *Learning Jupyter 5: Explore Interactive Computing Using Python, Java, JavaScript, R, Julia, and JupyterLab, 2nd Edition*. Packt Publishing Ltd.](http://paperpile.com/b/16YQp0/WK4E9)

[Zhang, Jihai, Wengang Zhou, and Houqiang Li. 2014. “A Threshold-Based HMM-DTW Approach for Continuous Sign Language Recognition.” In *Proceedings of International Conference on Internet Multimedia Computing and Service*. New York, NY, USA: ACM. https://doi.org/](http://paperpile.com/b/16YQp0/ii8V)[10.1145/2632856.2632931](http://dx.doi.org/10.1145/2632856.2632931)[.](http://paperpile.com/b/16YQp0/ii8V)

**TABLES AND FIGURES**

**Table 1.** The following table 1 consists of accuracies of a sample size of 10 for both the Dynamic Time Warping (DTW) algorithm and the Hidden Markov Models (HMMs) algorithm.

| **S.No** | **DTW** | **HMMs** |
| --- | --- | --- |
| 1 | 69.65 | 79.84 |
| 2 | 76.7 | 94.36 |
| 3 | 71.4 | 78.37 |
| 4 | 70.99 | 83.39 |
| 5 | 69.79 | 82.71 |
| 6 | 80.98 | 93.45 |
| 7 | 80.46 | 82.49 |
| 8 | 68.43 | 75.51 |
| 9 | 68.89 | 79.84 |
| 10 | 75.7 | 88.29 |

**Table 2**. The table below presents comprehensive statistics for two distinct groups, each comprising a sample size of N=10. The mean percentage accuracy achieved by the Hidden Markov Models method is documented at 83.83%, while the accuracy percentage attributed to the Dynamic Time Warping algorithm registers at 73.31%.

|  | **Groups** | **N** | **Mean** | **Std.**  **Deviation** | **Std. Error**  **Rate** |
| --- | --- | --- | --- | --- | --- |
| **Accuracy** | HMMs | 10 | 83.83 | 6.302 | 1.993 |
| DTW | 10 | 73.31 | 4.782 | 1.513 |

**Table 3**. Independent Sample t-Test for Accuracy Comparison with 95% Confidence Interval and Equal Variance Assumption

| **Levene’s Test for Equality of Variances** | | | | **T-test for Equality of Means** | | | | | **95 % Confidence Interval of the Difference** | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **F** | | | **Sig.** | **t** | **df** | **Sig (2-tailed)** | **Mean Difference** | **Std.Error Difference** | **Lower** | **Upper** |
| **Accuracy** | **Equal variances assumed** | .371 | .500 | 4.203 | 18 | .004 | 10.516 | 2.502 | 5.259 | 15.773 |
| **Equal variances not assumed** |  |  | 4.203 | 16.787 | .004 | 10.516 | 2.502 | 5.232 | 15.800 |

**Fig. 1.** The output of Dynamic Time Warping and the output of Hidden Markov Models.

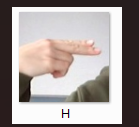
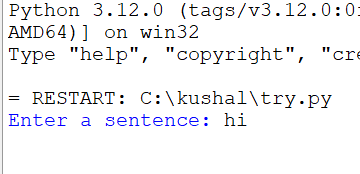
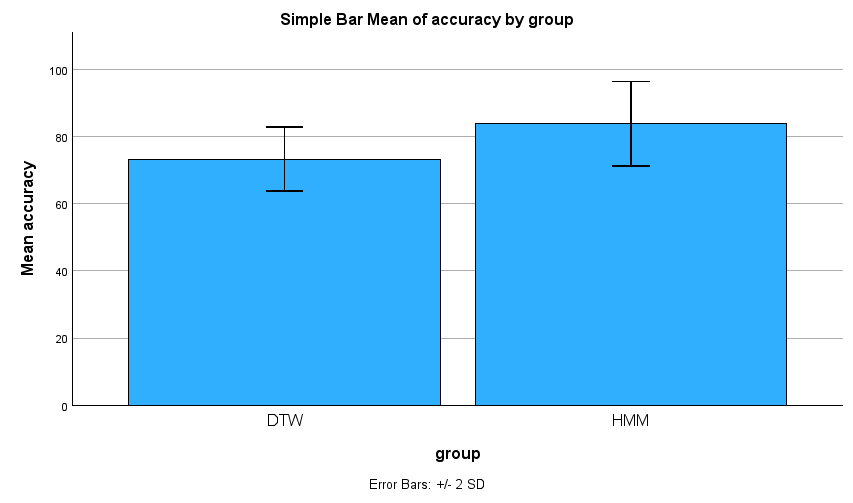
**OUTPUT :**

Fig. 2 Comparison of Mean Accuracies between Dynamic Time Warping and Hidden Markov Models Algorithms.This bar chart illustrates a comparison of mean accuracies, with the Y-axis representing accuracy values and the X-axis denoting the proposed and existing algorithms. The mean accuracy for the Hidden Markov Models is recorded at 83%, while the Dynamic Time Warping algorithm achieves an accuracy of 73%.



# **Hidden markov model architecture**



p(ti/ti-1) = Transition Probability, p(wi/ti) = Emission Probability