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Research paper

Fuzzy Temporal Rule-Based Natural Language Processing for Medical Text Analysis for Caring for Geriatric People

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Abstract

The development of robotics applications heavily relies on artificial intelligence and machine learning, which are prerequisites for creating intelligent robotic systems. Furthermore, the development of intelligent robots requires feature selection, classification, and fuzzy rule-based decision making. Because they immediately aid the elderly in receiving medical care, allowing them to go about their daily lives more quickly and effectively, medical assistive robots are beneficial to society. By removing characteristics that don't contribute, such as noise, null values in databases, and properties unrelated to classification problems, feature selection lowers the dimension of the data. Natural language processing can be utilized in medical applications, such as providing medical assistance through robot arm control, to handle the challenging task of directing the robot arm using elderly instructions or orders. To effectively convert speech to text and conduct morphological, syntactic, and semantic analysis on the converted text to more precisely detect the commands issued to robots by older adults, the Fuzzy Temporal Rule-based Semantic Analysis Algorithm (FTRSAA) is suggested in this study. Additionally, the efficient design and execution of the system that helps the elderly are made possible by this voice-activated robot control system, which utilizes the latest intelligent robot technology. By using these recently suggested algorithms to comprehend natural language texts generated from discussions, it communicates with older people.

Keywords: *Medical Application; Artificial Intelligence; Deep Learning; Fuzzy Temporal Rule-Based Semantic Analysis Algorithm.*

1. Introduction

According to the existing demographic landscape in India, it is anticipated that in the following years, the proportion of older adults to the total population will increase threefold above the current ratio. Nearly 104 million people in India are 60 years of age or older, comprising 53 million females and 51 million males, according to the 2023 Population Census of India [1]. According to a report released by the United Nations Population Fund (UNFPA) and HelpAge India (HAI), it is projected that by 2026, there will be 173 million older people living in India. They require support with their intellectual and physical tasks because of their advanced age. Like this, the issue of an aging population is one that many developed nations are also dealing with [2].

Furthermore, home and community-based health care services are a critical issue for seniors that academics studying robotics and medicine have noted. They anticipate receiving excellent care, such as independent living, and the indispensability of their presence within the family. 1,50,000 persons use wheelchair robots for assistance with activities of daily living (ADLs) in the United States alone [3]. Seniors are dealing with serious health issues in the new millennium, including cognitive decline [18]. The world's nations are designating specific care providers and companions for older people who require the potential of sociable, devoted, and assistive mobile robots because of the rise in economic and social demands placed on the elderly population [20]. According to the International Federation of Robotics (IFR), service robots are employed in a wide range of daily tasks, except for manufacturing operations. These robots perform helpful tasks for people with varying degrees of autonomy, ranging from partial autonomy, which involves human-robot interaction, to complete independence, which involves no human-robot intervention at all. Robots are automating repetitive and time-consuming tasks in the healthcare industry, such as teleoperation surgery, providing high-quality services for medical professionals, offering older adults personal assistance to support their physical and psychological well-being, and aiding people with disabilities in their physical recovery and rehabilitation [16]. The elderly population is driving the development of assistance robot devices for home services [4]. The most essential services are offered by this emerging sector of robotics, which encompasses social, assistive, and service robots and is defined using a variety of terms [19]. Entirely or semi-autonomously operated assistive robots contribute to human well-being. Although many assistive robots have been developed and are available on the market to help people with physical limitations, some unpredictable and dynamic circumstances are beyond their capabilities. The order of the remaining sections is as follows: Section 2 presents the background of the study; a summary of the suggested workflow is given in Section 3; Section 4 presents the findings and discussion; and Section 5 concludes the study in its final stage.

2. Background of The Study

The construction of contactless interface devices is made possible by object recognition systems that utilize both speech and vision. The benefit of this technology is remote engagement, which eliminates the need for elderly individuals to interact with an input device [21] physically. Because they enable the robotic system to become familiar with the user, both approaches offer the benefit of facilitating simple and natural user-robot interaction. Within the fields of robotics and artificial intelligence (AI), human-robot interaction (HRI) is a prominent and demanding field [5]. Artificial Intelligence (AI) is a broad field that encompasses various aspects of creating intelligent machines, such as knowledge representation schemes, search algorithms, logic-based inference techniques, rule engines for expert system development, robot planning algorithms, learning algorithms, Natural Language Processing (NLP), and image processing techniques. With the application of recent methods, such as Hidden Markov Models (HMM), Artificial Neural Networks (ANN), Fast Fourier Transforms (FFT), and Learn Vector Quantization (LVQ), speech recognition systems have revolutionized human and robot communication in recent years [6]. The power of this speech recognition technology, which is based on sophisticated Machine Learning (ML) algorithms, and the most recent advancements in its implementation have helped it gain popularity. Most contemporary apps, including home automation and smartphones, require the user's speech to be processed [22]. When faced with such a situation, voice recognition devices can utilize assistive technology to process data offline, enabling safe and independent operations. NLP is an essential addition to AI, as it enables computers to comprehend human language through various stages of processing [23]. In robot control, NLP is more useful for controlling the robot using speech recognition, which is a challenging task. Nonetheless, NLP greatly facilitates Human-Computer Interaction (HCI), making command-based robot arm control more appropriate [7]. As a result, it is regarded as the most critical technology for designing medical robots and a long-held goal. Natural language processing can be used to solve the challenging task of controlling a robot arm by an elder's instructions or commands in dynamic environments, such as robot arm control [24]. Controlling the interfaces and optimizing the algorithms are two major design issues in voice recognition systems. Elderly individuals can utilize the voice control technologies found in sophisticated robots to carry out more intricate tasks with high degrees of freedom for optimal performance. [8].

Natural Language Processing (NLP) in robotics, and more specifically, in elderly care (among other applications), has been a subject of significant advances through various algorithms, including Hidden Markov Models (HMMs) and rule-based systems. Nevertheless, these methods have inherent limitations, including a lack of flexibility, context sensitivity, and responsiveness to changing environments. The Fuzzy Temporal Rule-Based Semantic Analysis Algorithm (FTRSAA) addresses the limitations above by integrating fuzzy logic with temporal constraints, enabling the system to better interpret ambiguous and context-dependent commands compared to traditional systems. For example, Bastianelli et al. (2017) utilized Spoken Language Understanding (SLU) systems based on pre-made rules and models to process commands. Although successful in controlled environments, their system performs poorly in dynamic environments, particularly when the robot must respond to changes in the environment in real-time or when it must adapt to changes in the user's speech or language. Likewise, Abdel-Hamid et al. (2014) also employed a CNN-HMM hybrid system for speech recognition in robotics; however, this system, although convenient, lacks a temporal aspect to enhance understanding of commands over time. The FTRSAA approach, on the other hand, utilizes fuzzy temporal rules, which enable it to describe the temporal and spatial relationships of the commands more effectively. The rules help the system adapt to variations in user speech patterns and environmental settings, thereby enhancing the accuracy of the semantic features and increasing its flexibility in responding. FTRSAA can handle multi-step commands more effectively, such as "Pick up the cup and place it on the table," due to its use of fuzzy logic to handle uncertainty in speech recognition and temporal logic to manage task sequences.

Recent developments in the field of fuzzy logic and NLP also highlight the advantages of the FTRSAA approach. For example, Zhao et al. (2023) investigated the use of fuzzy systems to enhance the robustness of speech recognition in eldercare robots, demonstrating that a combination of fuzzy logic and NLP can improve the accuracy of command recognition and system adaptation to various elderly users. Furthermore, Tan et al. (2023) applied fuzzy semantic analysis to the robotics system, demonstrating its ability to process ambiguous commands as input for elderly users. FTRSAA was able to process variations in speech patterns and comprehend complicated commands. These new investigations highlight the applicability of fuzzy logic in enhancing the functionality of NLP systems in dynamic and unpredictable conditions, which is particularly relevant in the context of robotics for providing care to older adults. The combination of fuzzy logic, temporal, and spatial constraints gives FTRSAA a clear edge over conventional rule-based and HMM methods. It addresses major flaws in previous models, including inflexibility, the inability to handle dynamic interactions, and a limited ability to comprehend complex, context-sensitive commands. This makes FTRSAA especially applicable to the practical implementation of assistive robots that can assist older people as they go about their daily lives with minimal support.

3. Proposed Framework

By microphone, the user speaks commands to the robot. This technology can identify the command and recognize the user's voice. Additionally, the voice-to-text conversion module receives the identified commands and uses them to translate the voice input into corresponding text input. Here, a novel algorithm is proposed to comprehend commands issued in Natural Language (NL) and to effectively translate voice to text, utilizing training data to learn about the current state of the world. The transformed text is cross-checked against a knowledge base that contains the maximum amount of text commands that can be entered for various voice input types [9]. The NL framework created in this study may distinguish between two scenarios: (a) The planner gives the robot a description of the outside world (the bottle is on the table); and (b) Obtaining human input (verify the location and object's distance from the robot's present position with the user). Here, the Decision Manager (DM) receives the commands generated by the NL framework. By comparing the result with the position of every object, the DM must confirm the outcome. Subsequently, the decision manager verifies the object's location and the associated spatial limitations before instructing the robot. If the object's location is unknown, the DM offers alternate suggestions [25]. The context-based NL approach used in this work is what the DM provided for feedback. The robot will wait for the user to approve or reject any additional suggestions made via the direct message. The DM will update the domain and modify the input objective accordingly after the user confirms and accepts the new alternative plan. The text analysis includes syntax analysis, semantic analysis, PoS tagging, and stemming. [10].

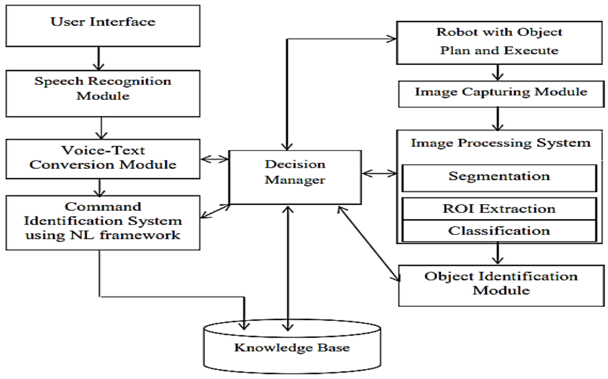

Fig. 1: Overall Architecture.

Pre-processing: The pre-processing stage separates the textual documents into tokens, which are then forwarded to the POS tagging module for the addition of POS tags. Furthermore, the Porter stemming technique is utilized to identify the root words by stemming [26].
Parts of Speech (PoS) Tagging: When performing PoS tagging, the labeling task involves checking each word in the phrase and assigning the appropriate part-of-speech label to each one. Furthermore, the PoS tagger for every word is determined by its placement within the grammatical context [27]. This module utilizes the Corpora PoS tagger to tag words more efficiently, aided by a dictionary. The grammar for basic statements like "I eat," "he goes," "Ram walks," "it runs," "he drinks," and so on is used to determine whether the noun-verb sentences in the preceding grammar are grammatically correct. In this manner, the context-free grammar specified for English language phrases is used to do the syntax testing for the complete set of instructions [28].
Additionally, the semantic analysis module used in this study effort is employed to analyze semantics. By identifying the keywords, the semantic analyzer helps the robot comprehend the meaning of the command. This causes the robot to extend its arm in the direction of the food, pick it up from a dish, and give it to the user. In this study, anaphora resolution is employed to perform semantic analysis on single sentences, followed by multiple sentences based on the preceding commands [29].
Syntax Analysis: All syntactically relevant terms are extracted using syntax analysis, except the verb, adverb, pronoun, adjective, preposition, and conjunction. Additionally, it helps remove the unnecessary words from the input texts.
Semantic Analysis: By using semantic analysis, one can deduce a sentence's meaning from its context. In this work, the noun phrase is identified by the semantic analyzer from the provided input sentence, and it is subsequently transformed by it into a portion of the command. Additionally, it utilizes the speech recognition capability to analyze the following few words in the phrase by converting them from speech to text [11]. Suppose it satisfies the task according to the robot's state or behavior. In that case, it will be considered as the principal verb of the sentence given by the user as a command. Here, the entire definition of robot tasks is designed by employing specific functions along with the requisite arguments related to the relevant roles and is semantically significant with respect to the robot task. By identifying the verbs that are used to satisfy the needs of the object, start time, instrument, actor, and destination place, it also defines the available grammatical structures and the meaning of the sentences. When the provided input statements only specify one task, the rules are applied to word fragments from the input sentence to deduce the meanings of such phrases. [12].

Fuzzy Temporal Rule-based Semantic Analysis algorithm (FTRSAA)	
Input: Syntax Analyzer processed User Voice	
Output: Robot command Text	
1.	Examine the Syntax Analyzer's production.
2.	Use a triangular membership function and a linguistic variable to perform fuzzification.
3.	Temporal and spatial limitations combine to form the CNN's Low, Medium, and High settings.
4.	Utilize instant and interval comparison to apply spatial and temporal limitations.
5.	Use the rules to analyze the words.
6.	Determine the command's semantically related words.
7.	Go back and finish

Tagging parts of speech and eliminating stop words are two aspects of performing syntax analysis. The remaining words in the phrases are categorized as features under several groupings. "Robot," "eat," and "food" are the features that were chosen from the text. Place markers, norms, and temporal and spatial limitations are used in the semantic analysis that follows the syntax analysis. After the semantic analysis, pragmatic analysis is performed when the query consists of many sentences. [13].

3.1. Fuzzy temporal CNN architecture

A collection of max pooling layers and a set of convolution layers make up the main components of a convolutional neural network (CNN). The input sentences are made up of a total of features that have been assembled from several feature maps. Moreover, the use of more convolutional and pooling techniques, along with fuzzy and temporal constraints, is causing the feature map sizes to decrease at the upper layers. To integrate the chosen features from the input text, this model adds four more fully linked hidden layers on top of the last CNN layer [14]. The posterior probability values are computed and used for maximum likelihood estimation by applying the Hidden Markov Model (HMM) [17]. Lastly, the continuous stream of voice units is recognized and converted into text format using the Viterbi algorithm. FTRSAA (Fuzzy Temporal Rule-Based Semantic Analysis Algorithm) is an algorithm that uses fuzzy logic with temporal constraints to understand voice commands of older adults. This helps the robot interpret and perform sophisticated tasks, particularly in cases of uncertainty or ambiguity in the command. Fuzzy logic is used to handle unclear or imprecise input, enabling the robot to execute commands in the correct order, considering both time and space.
Fuzzification,

$\mu A(x) = \frac{\max(0{,}1|x-c|}{\Delta}$ Where $\mu A(x)$ represents the degree of membership of the command x in fuzzy set A centered at c with width Δ.

The algorithm operates by analyzing the voice command through a syntax analyzer, which breaks down the text into its meaningful components. Following this, semantic analysis is performed, in which the robot interprets the command's meaning using a set of predefined rules. The temporal and spatial constraints are used to guide the robot in performing the correct actions in the proper sequence, based on real-time factors such as the object's location and the interactions between the user and the robot.

3.2. Fuzzy temporal CNN structure

The Fuzzy Temporal CNN Architecture is based on processing input voice commands using fuzzy logic and deep learning. This architecture leverages the strengths of convolutional neural networks (CNNs) combined with fuzzy temporal rules, enabling the robot to respond effectively to voice commands, even in dynamic environments where the user's speech rate may lack clarity or precision.
Convolution Layer Output,

$\mathrm{Output} = \sum(\mathrm{I} * \mathrm{K}) + \mathrm{b}$Where I is the input signal (voice command), K is the kernel (filter), and b is the bias term.

The structure consists of multiple layers that incorporate convolutional operations to extract features from the input speech. These characteristics are further passed to the fuzzy logic layers, which implement temporal and spatial constraints, enabling the robot to recognize and act accordingly in the appropriate context. The CNN layers help reduce the data's dimensionality, and the fuzzy layers help mitigate the uncertainty in command processing. These techniques, when combined, provide a system capable of high accuracy and efficiency in responding to voice commands in real-time.
Dataset: This paper utilizes a voice command dataset to train and test the proposed Fuzzy Temporal Rule-Based Semantic Analysis Algorithm (FTRSAA) for controlling a robot based on instructions from older adults using natural language. The dataset has been designed to meet the needs of older users, offering both easy and challenging voice commands. This data plays a significant role in ensuring the system works well once it is implemented in the real field, where older people will be the participants.
The data consists of 1,2001,200 voice commands collected from 100 elderly individuals. The voice commands are evenly distributed among various categories, ranging from basic ones, such as "Pick up the cup," to more complicated ones, such as "Move the cup to the kitchen table. "The dataset includes a wide variety of instructions that the robot must process to complete various actions in a home environment.
The dataset originated from field recordings conducted in collaboration with senior care facilities throughout India. These were recorded in controlled surroundings, and the background sounds were as much as possible eliminated to make the voice commands clear. The dataset is designed to be representative of the real-life conditions that older people may encounter when interacting with assistive robots in their homes.
The voice commands used in the dataset are primarily in English, as it is a widely spoken language among older adults in India. Nevertheless, to make the dataset more diverse and mitigate the effects of the region's multilingual population, some commands were also documented in the local languages, such as Kannada and Hindi. This is because the system will be able to comprehend a broader range of elderly participants, as it is multilingual. Thus, it will serve the diverse linguistic backgrounds of these participants.
The set contains commands of different complexity. The simple command, such as the one given below, is often mixed with complex and multi-step commands, for example, a command like "pick the book on the table and put it on the shelf." This complexity difference is crucial to ensure that the proposed system can process both complex and straightforward instructions, such as those an elderly user may provide in real life.
The older adults in the dataset are diverse, ensuring the data is robust and reliable. The sample size consists of participants aged between 60 and 80 years, with 60% of the participants between 60 and 70 years, and 40% above 70 years. Moreover, the dataset is quite diverse in terms of health conditions, as it includes participants with mild cognitive impairments and hearing impairments. This variety will ensure that the model is put to the test with a broad spectrum of users, as it will be more adaptable to reality, which is particularly important for elderly adults who may experience various health issues.
To clean the voice records, the voice data was recorded and processed after removing noise and irrelevant voice data, such as background chatter. The voice commands were transcribed into text using speech-to-text conversion software and then manually corrected to ensure accuracy. The textual data was then subjected to stop-word elimination and stemming using the Porter Stemming Algorithm to reduce words to their root form, allowing for more effective analysis.
The data were divided into training and testing sets with 80 an 20 ratio. The FTRSAA model was trained on the training set, and the system was subsequently tested on the testing set to evaluate its success in recognizing and responding to voice commands issued by elderly participants. This division ensures that the model is trained on a large sample size and has been extensively tested on unseen data to quantify its generalization capabilities.

4. Experimental Results and Discussion

The system has been trained using a variety of machine learning methods and tested using natural language commands. This section displays the findings from the suggested work. We used the Precision-Recall metric to assess the classifier's output quality [30]. The stark disparity across the courses provides a helpful indicator of success prediction. Recall is a measure of how many truly relevant results are rewarded in information retrieval, whereas precision is a measure of how applicable the results are. Several experiments have been conducted using the proposed methodology for evaluating the system [15]. Figure 2 compares the accuracy of the proposed NLP_CNN work for five tests with the previous work by Spoken Language Understanding (SLU) Chain Bastianelli et al. (2017), CNN HMM Abdel-Hamid et al. (2014), and the Dynamic warping algorithm Davis et al. (1980).

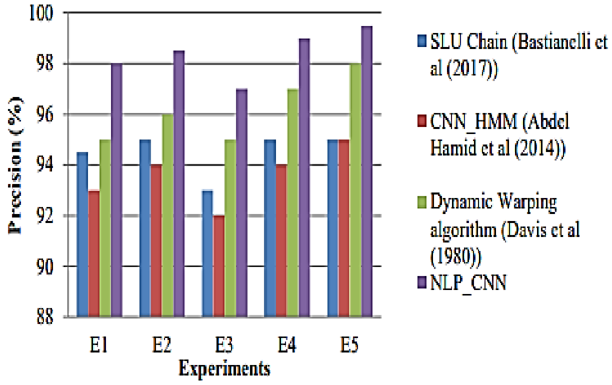

Fig. 2: Performance Analysis Using Precision Values for NLP Algorithms.

Comparative accuracy of NLP CNN to previous systems (Spoken Language Understanding, CNN-HMM, Dynamic Warping) of voice commands with a varying range of the object (5090 cm). The accuracy of the NLP-CNN model demonstrates better command recognition accuracy over varying distances than current models.

Figure 2 illustrates the accuracy values of the proposed NLP-CNN methodology in comparison to existing techniques, including Spoken Language Understanding (SLU), CNN-HMM, and Dynamic Warping. These tests were conducted using voice control of a robot at various distances from the objects, ranging from 50 to 90 cm. The findings indicate that the NLPCNN model is significantly superior to current methods in terms of command recognition accuracy, particularly in situations where object distances increase.

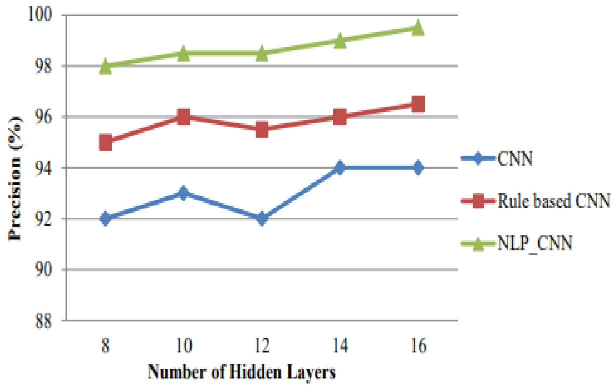

Fig. 3: Comparisons with Precision Values.

Comparison of precision values of NLP_ CNN and other prior studies by Bastianelli et al. (2017), Rule-based CNN, and machine learning training methods. This is compared to five tests on Kinova Jaco2 robots, which are used for voice-controlled tasks. Figure 3 compares the precision values of the proposed NLP CNN system with those of prior systems, including the rule-based CNN and the model introduced by Bastianelli et al. (2017). The experiment was conducted with the assistance of the Kinova Jaco2 robots, focusing on five trials in which voice inputs were used to control the robot. The NLP CNN approach proved to be more precise in all tests, a testament to its effectiveness in the real-world application of robots.

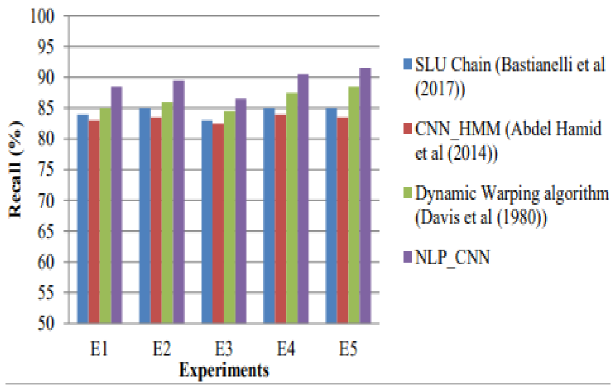

Fig. 4: Performance Analysis Based on Recall Values for NLP Algorithms.

The proposed NLP CNN approach and its recall values, compared to prior studies (Bastianelli et al., 2017; Abdel-Hamid et al., 2014; Davis et al., 1980) on voice commands, demonstrate the system's effectiveness in accurately recognizing relevant tasks.

Figure 4 displays the recall of the NLP-CNN model in comparison to past systems in robotic voice command recognition. Recall shows the percentage of correct optimistic predictions made by the system, and the value indicates that NLP_CNN proves to be more effective than the previous models in identifying relevant commands, particularly those that are more complex under dynamic conditions.

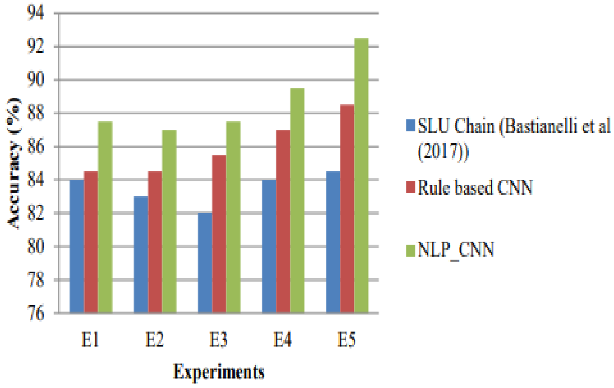

Fig. 5: Recall Comparison Analysis.

Comparison of the recall values of the proposed NLP CNN model and past approaches (Bastianelli et al., 2017; Abdel-Hamid et al., 2014). The figure illustrates how semantic and syntactic analysis enhance the rate of recall in voice-controlled robot familiarization.
Figure 5 is used to compare the values of the proposed NLP model (CNN model) with the past approaches in terms of recall. The graph illustrates that the inclusion of semantic and syntactic analysis in NLP significantly enhances the benefits of the CNN, particularly in terms of recall, especially when it comes to enabling the robot to follow multi-step instructions or instructions that depend on the situation.

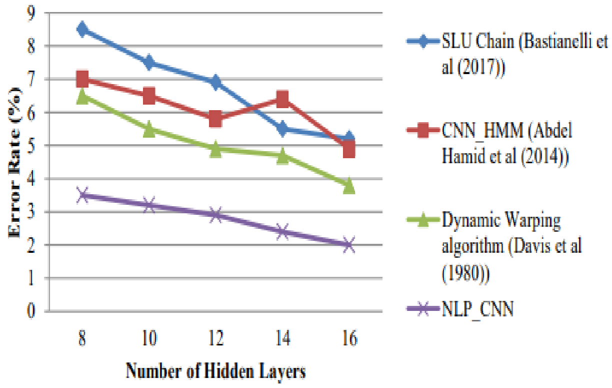

Fig. 6: Error Rate Analysis.

Regardless of which method proves to be more effective in verifying voice command recognition, the NLP CNN is superior to previous methods suggested by Bastianelli et al. (2017), Abdel-Hamid et al. (2014), and Davis et al. (1980), with lower error rates.
Figure 6 presents a comparison of the error rates between the proposed NLP-CNN system and those reported in previous research. The NLP_CNN is less prone to error, as the voice command recognition system demonstrates high accuracy and reliability in real-life use.

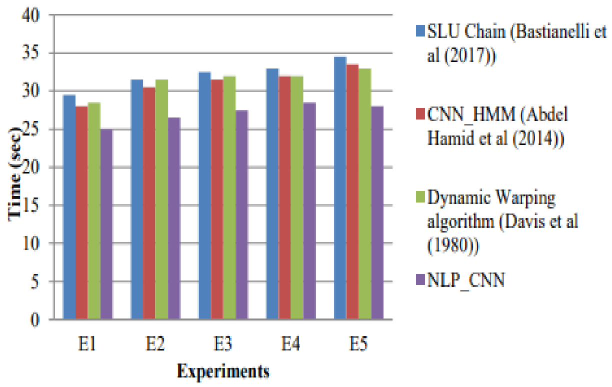

Fig. 7: Time Analysis for Picking Up the Objects.

The NLP_CNN system was used to analyze the time spent selecting and picking up objects at different distances (50-90 cm) compared to the past works. The figure illustrates how the proposed system minimizes service time during task execution.
Figure 7 indicates the time the NLP_CNN system required to collect objects at different distances, in comparison with the performance of the methods used in the past. The time analysis indicates that the NLP_CNN system significantly reduces the time required to execute tasks, thereby enhancing the system's efficiency when performing tasks such as object retrieval in elderly care applications.

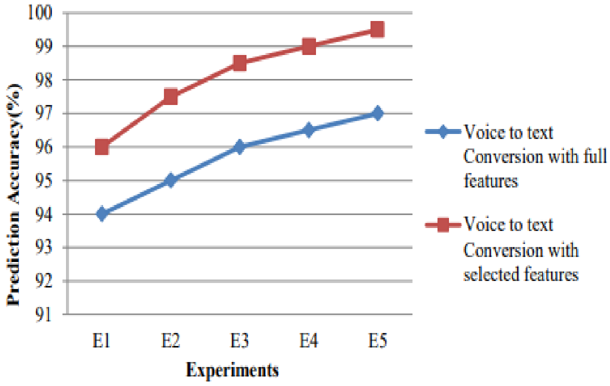

Fig. 8: Voice-to-Text Conversion Performance Analysis.

Voice-to-text conversion performance of NLP CNN, accuracy of all features, and selected characteristics in five tests. The number indicates that the system can accurately convert voice instructions into text.
Figure 8 shows the accuracy of voice-to-text conversion of the NLP_CNN system. The test is conducted over five tests, during which the system becomes busy interpreting voice commands and converting them to text. This discussion confirms that the NLP-CNN method is highly accurate in recognizing and transcribing voice commands among elderly users.

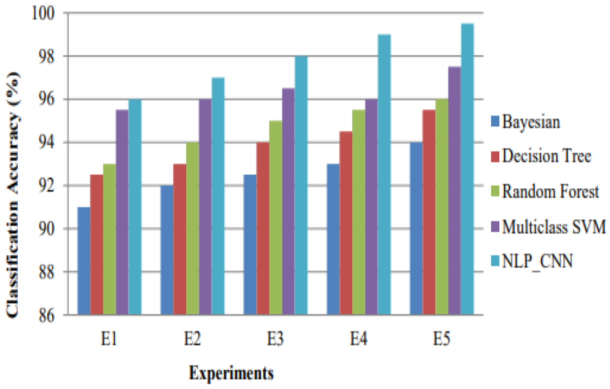

Fig. 9: Classification Accuracy Analysis.

Comparison of the classification accuracy of the proposed method, NLP_CNN, and existing classifiers (Bayesian, Decision Tree, Random Forest, Multi-class SVM). As indicated in the figure, the NLP_CNN system has improved its accuracy by 5%.
Figure 9 compares the accuracy of the NLP_CNN system in classification with that of other popular machine learning classifiers, including Bayesian, Decision Tree, Random Forest, and Multi-class SVM. This analysis reveals that the NLP CNN model outperforms these classifiers by 5, demonstrating its ability to excel in voice command classification problems for robot systems.

5. Conclusions

This paper proposes an intelligent classification system for position prediction along with a natural language processing approach. The Kinova Jaco2 robot, the ROS operating system, the C++ programming language, the NLP toolkit, lexical corpora-based POS tagging, and the Porter stemming algorithm were all used in the development of the robotic system. This job has been assigned using artificial intelligence approaches, including machine learning and natural language processing, and it has been compared to similar robot work. The research work's outcomes demonstrate that the suggested system outperforms other related systems in terms of object prediction accuracy. Additionally, the suggested NLP_CNN intelligent robotic system shortened the total service time for the older adults' pick-and-provide services, which are necessary to deliver vital medical and other services to them.
The significant issues to be considered in future research are multilingual command processing and real-time performance in noisy environments. The transfer learning method may enhance the accessibility of a multilingual FTRSAA framework by adapting the system to various languages with a minimal amount of data. This would assist the model in identifying commands from aged users with different language backgrounds. Additionally, to enhance real-time performance in dynamic settings, noise-responsive speech recognition algorithms, such as deep neural networks (DNNs), can be integrated to remove background noise and ensure robust voice command recognition in noisy environments. Moreover, elderly care robotics should be ethically focused. Further developments should be based on privacy, data security, and informed consent, ensuring that user data is preserved and that robots are used as an aid to human caregivers, not as a replacement. The user experience could also be improved by adaptive learning systems that are capable of personalizing interactions depending on the unique speech patterns and cognitive needs of the individual. The use of reinforcement learning or online learning methods may help the system evolve and enhance its performance over time, transforming the robotic assistant into a more efficient and responsive device that meets the individual needs of each elderly user.

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