International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

An Automated Speech Recognition System Using Whale Optimized Random Forest Algorithm

[1]Urvashi Rawat, [2]Adlin Jebakumari, [3]Ramesh Chandra Tripathi, [4]Dr. Purnima Nag

Submitted: 20/08/2023 **Revised**: 09/10/2023 **Accepted**: 20/10/2023

Abstract: Automated speech recognition (ASR) systems play a significant role in applications for natural language processing and human-computer interaction. The richness and variety of speech signals, however, make it difficult to improve the ASR systems' accuracy and effectiveness. This study describes an ASR system that uses the Whale Optimized Random Forest Algorithm (WO-RFA) algorithm to improve speech recognition performance. The suggested ASR system combines the strength of random forest algorithms with the optimization capabilities of the Whale Optimization Algorithm (WOA). The WOA is a nature-inspired metaheuristic algorithm based on humpback whale social behavior. It simulates whale hunting behavior to find the best solutions in a given search space. The system intends to improve the accuracy and resilience of speech recognition by incorporating WOA into the random forest algorithm. Noise removal, feature extraction, and normalization techniques are used to preprocess the speech data. This step gets the data ready for training and recognition. Preprocessed speech signals are analyzed to identify relevant information. The characteristics were extracted using MFCC, or Mel Frequency Cepstral Coefficients. To enhance the random forest's performance in voice recognition tasks, the WOA modifies the random forest's parameters and structure. To enhance the model's precision and effectiveness, the method alters hyper parameters such as the number of trees, tree depth, and splitting criteria. The ASR system incorporates the improved WORF model, allowing it to convert speech inputs into text outputs in real-time. The technology can be used for a variety of purposes, including voice assistants, transcription services, and voice-controlled systems.

Keywords*: Automated Speech Recognition (ASR), Whale Optimization Algorithm (WOA), Whale Optimized Random Forest Algorithm (WO-RFA), Mel Frequency Cepstral Coefficients (MFCC), natural language processing*

1. Introduction

Numerous programmes enable automatic identification of people based on their distinctive physiological or behavioral traits. To identify people, a variety of behavioral biometric methods can be utilized, such as gait analysis, voice recognition, mouse use patterns, signature analysis, keyboard dynamics, and many other cognitive biometrics. Created a context-free digital pen-tablet sensor, an approach for analyzing handwritten input in real time, and an effective feature selection strategy [1]. A challenging health problem that affects people all over the world is depression. The World Health Organization (WHO) estimates that it is currently the fourth-leading contributor to disability and will surpass all other contributors by 2030. People who suffer from depression are less productive and attempt suicide at alarmingly high rates. It is crucial to recognize depression early so that prompt treatment can save lives since depressed persons are more likely to have suicidal thoughts. A list of typical signs to recognize depression is provided in the Diagnostic and Statistical Manual (DSM) of Mental Disorders, a publication of the American Psychiatric Association. Frequently used by doctors, the Hamilton Rating Scale for Depression (HAMD) is a well-known subjective test [2]. A wide range of behavioral biometric techniques, including gait analysis, voice recognition, mouse use patterns, signature analysis, keyboard dynamics, and many more cognitive biometrics, can be used to identify individuals.

As a context-free digital pen-tablet sensor, a real-time method for handwritten data analysis, and an optimal feature selection technique. After examining the most cutting-edge techniques for computer mouse dynamics, an effective machine learning and neural network strategy for dynamic user authentication was provided [3]. Modern ASR systems frequently partition speech recognition into several distinct jobs, each of which is individually optimized. Based on knowledge of speech production and perception, Mel First accomplishes a specialized recovery of the MFCCs or perceptual linear prediction (PLPs) cepstral features from the short-term speech signal. Then, as subword units are frequently based on phonemes, a statistical model that either establishes or distinguishes the relationship between the attributes and them is applied to estimate its likelihood. The best matched word hypothesis is then found by

[1]*Assistant Professor, School of Engineering and Computer, Dev Bhoomi Uttarakhand University, Uttarakhand, India, Email Id: socse.urvashi@dbuu.ac.in*
[2]*Assistant Professor, Department of Computer Science and IT, Jain (Deemed-to-be University), Bangalore-27, India, Email Id: j.adlin@jainuniversity.ac.in*
[3]*Professor, College of Computing Science and Information Technology, Teerthanker Mahaveer University, Moradabad, Uttar Pradesh, India, Email id: rctripathig@gmail.com*
[4]*Professor, School of Engineering & Technology, Jaipur National University, Jaipur, india, Email Id: purnima.nag@jnujaipur.ac.in*

combining lexical and syntactic limits given the likelihood estimates of the subword units [4]. Finally, by integrating lexical and syntactic limitations, the best matching word hypothesis is found while taking into account the likelihood estimates of the subword units. These elements are combined into a single neural network by the end-to-end (E2E) model. Overcoming the sequence labeling issue between variable-length speech frame inputs and label outputs simplifies the development of ASR systems and improves the efficiency of ASR operations [5]. An ASR system, also known as a speech-to-text system, is a technology that converts spoken language into written text. It is designed to recognize and interpret human speech patterns, allowing computers to understand and process spoken words. ASR systems are commonly used in various applications, including transcription services, voice assistants; call centers, voice-controlled devices, and more. [6]. In contrast to other command-line contacts or graphical-based interactions, speaking commands to machines is more appropriate and practical, which has made human-machine interaction (HMI) a well-liked research field throughout the previous 50 years. The technique of converting spoken words into their written equivalents is called speech recognition. It also makes it possible for humans and machine connection. How resilient the ASR system is will depend on how accurate it is, which must be strong in any kind of ambient or changeable state. Dictation, SIRI, ALEXA, Google Assistant, automatic call processing, and other features are used by ASR [7]. ASR systems have substantially improved thanks to DNNs. The ASR system uses a decoding algorithm that blends language and acoustic models to produce the most likely word order that corresponds to the input voice. To discover the most likely transcription, a large collection of potential word sequences must be searched through [8]. Over the past several years, the effervescence of all the fields that employ neural networks to carry out some well-known tasks, such as voice processing, computer vision, and so forth, has increased. One of these fields is ASR, which has achieved significant advancements. There are numerous implementations currently in use, some of which draw from related domains, and the outcomes continue to improve [9]. The study [10] provided the evidence of the advantages of using Deep Neural Network methods to voice recognition systems. The Kaldi framework is used to create hybrid DNN for Punjabi voice recognition. The automatic speech recognition system performs much better when DNN is used, and Karel's DNN model also outperforms Dan's DNN model in terms of recognition performance. Compared to the PLP feature, the MFCC feature yields superior results [10]. The Hidden Markov Models HMM-DNN model and the end-to-end deep learning model have recently outperformed the HMM-GMM model in terms of performance. [11]. Due to a lack of data, ASR systems perform less well with low-resource languages. Wider context coverage has been achieved by the use of multilingual training, which has been shown to perform better than monolingual training. [12]. Voice technology needs to be developed for languages with minimal resources. For the underdeveloped Angami language, they discuss creating a voice corpus and an autonomous speech recognition system in the study. The voice corpus and speech recognition technology were developed as a result of the variety of Angami spoken in Kohima hamlet [13]. The study [14] suggested an innovative end-to-end audiovisual ASR (AV-ASR) multitasks learning system . A system for ASR serves as the cornerstone of contemporary speech-based technologies. The ambient acoustic noise, however, may considerably impair the effectiveness of an ASR system. This problem can be solved unusually by including visual qualities that define lip movements in conventional audio-based ASR systems. The four Ethiopian languages represented in the study utilizing speech recognition software are Amharic, Tigrigna, Oromo, and Wolaytta. They employed evaluation corpora of roughly an hour each for each language and training corpora of 20 to 29 hours of speech. Different lexical and grammatical models with varied vocabulary sizes have been created for Amharic and Tigrigna. The training lexicons have been used to decode Oromo and Wolaytta. To reduce the relative word error rate (WER), which ranged from 15.1% to 31.45% for all languages, they used DNN based acoustic models [15]. The essay provides evidence of the advantages of using Deep Neural Network methods to voice recognition systems. The Kaldi framework is used to create hybrid DNN for Punjabi voice recognition. We use two strategies, taking use of the acoustic commonalities between Indian languages. A DNN can learn to translate smartphones or phones between different languages [16]. The study [17] suggested the Korean speech recognition system that is autonomous from beginning to end and hybrid CTC-attention network based. Hidden Markov models and deep neural networks have made substantial advancements in speech recognition systems. However, creating voice recognition for fresh applications is challenging for amateurs. Speech recognition systems have been streamlined into a single-network architecture using end-to-end methodologies. These methods can be used to create voice recognition systems without the need for specialist knowledge. For spoken dialogues in emergency call centers, the study looked into and assessed a variety of automatic voice recognition systems, labeling strategies, and acoustic and linguistic modeling methodology. Therefore, in order to effectively recognise conversation utterances, the fundamental components of speech recognition systems, such as language models, acoustic training techniques, and symmetric data labelling approaches, have been investigated and reviewed [18]. In this work, we discuss a random forest algorithm with Whale optimisation used in an automated voice recognition system.

2. Methodology

In this method we discuss about the speech recognition system using Whale optimized random forest algorithm MFCC.

2.1 Data set

Data from Switchboard, Fisher, Gigaword, Broadcast News, and Conversations are used to train the language model (LM), which is made accessible for public use. It has an 85K word vocabulary and 36M 4-grams. The two training datasets used are SWB-300, which has a 30 GB capacity and more than 300 hours of training data, and SWB-2000, which has a 216 GB capacity and more than 2000 hours of training data. The two sets of training data are stored in HDF5 format. The test set is made up of 1.6 hours of call home data and 2.1 hours of switchboard data from the Hub5 2000 evaluation set [19].

2.2 Data Preprocessing using Min Max Normalization

Scaling numerical characteristics within a certain range is often done using min-max normalization. It is often used to get data ready for models in machine learning. Min-max normalization used to normalize the input characteristics of the dataset for diabetes prediction.

Min-Max normalization is a technique of normalizing that uses linear modifications to the original data to provide a fair comparison of values before and after the procedure.

$$X_{new} = \frac{X=min}{max(X)-min(X)} \quad (1)$$

X_{new}=The adjusted value obtained after scaling the data

X=outdated value

$Max(X)$ = Dataset's highest possible value

$Min(X)$ = Dataset's lowest possible value

2.3 Whale optimized random forest Algorithm (WO-RFA)

The WOA is a metaheuristic algorithm that draws inspiration from humpback whale hunting tactics and natural phenomena. It is an algorithm for population-based optimisation that copies the social interactions and behaviours of whales. In order to find the best solutions to optimisation problems, the algorithm simulates the movement and behaviour of humpback whales. Based on the name used, it would seem that the "Whale Optimised Random Forest" algorithm is a hybrid of these two methods, where the Random Forest algorithm is modified in some way using the WOA. It is challenging to give more precise information about the precise implementation or performance of such an algorithm without more information or references, though. Popular ensemble learning method Random Forest blends different decision trees to produce predictions. It creates a vast number of decision trees during the training phase and averages each of their individual outputs in order to produce predictions. Random feature subsets are considered at each split to promote variance among the trees, and each decision tree is trained using a different subset of the data. The algorithm effectively quickens the rate of optimization, and the WOA's search approach also offers certain benefits for certain problems. It goes through the following stages: encircling the prey in phase one; spiraling in phase two; and hunting for prey in phase three.

2.3.1. Embedding Prey

The WOA selects the best search agent first, then locates and encircles its victim. Other search agents might migrate depending on the greatest search agent. Equations (1) and (2) in particular best capture it:

$$C = |D^{\to}.w^{\to *}(s) - w^{\to}(s)| \quad (1)$$

$$w^{\to}(s+1) = w^{\to *}(s) - B^{\to}.C^{\to} \quad (2)$$

where

$w^{\to *}$ is the most accurate location vector found, $w^{\to}$ is the position vector, while Equations (3) and (4) are used to determine B and C, which stand for the coefficient vectors:

$$D^{\to} = 2q^{\to} \quad (3)$$

$$B^{\to} = 2q^{\to}q^{\to} - b^{\to} \quad (4)$$

where

$q^{\to}$ stands for a random vector, a linearly decreases from 2 to 0 with the progress of the iteration, and $q^{\to}$ represents a random number between [0, 1].

2.3.2 Bubble Spiral

Equation (5) shows how to utilize spiral foam hair to catch prey and build spiral equations based on how far away the whales are from their prey:

$$w^{\to}(s+1)=C^{\to r}.f^{as}.\cos(2\pi l) + w^{\to *} \quad (5)$$

where

$C^{\to '} = |w^{\to *}(S) - w^{\to}(S)|$ is the separation between a whale's prey and it, a is a constant that determines the logarithmic helix's form, and s is a random vector distributed uniformly within [–1, 1].

Based on the likelihood o, the WOA decides between bubble net predation and confined confinement.

Equation (6) is so as follows.

$$w_x(s+1) = \begin{cases} w_o(S) - B.C & P \leq 0.5 \\ D.f^{as}.\cos(2\pi l) + w_o(S) & P \geq 0.5 \end{cases} \quad (6)$$

Where P $\epsilon[0,1]$ indicates the likelihood of the predation process.

2.3.3. Searching for prey

A global search is necessary per the WOA. Here are equations (7) and (8):

$$C = |D^{\rightarrow}.w^{\rightarrow}{}_{rand}(s) - w^{\rightarrow} \quad (7)$$

$$w^{\rightarrow}(s+1) = |w^{\rightarrow}{}_{rand} - B^{\rightarrow}.C^{\rightarrow} \quad (8)$$

Where $w^{\rightarrow}{}_{rand}$ represents a random position vector

As a result, in this work, the WOA was employed to maximize the RF's capacity to forecast the risk of invalidation associated with backfilling pipelines.

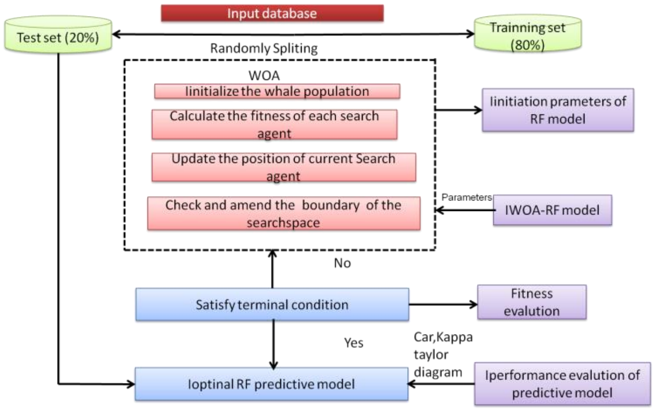

Fig.1. The hybrid classifier model WOA-RF

The WO-RFA model's optimization analysis procedure is depicted in Fig.1. The RF model's parameters determine each whale position vector. The WOA outputs the final parameters of the RF model after iterating the global optimal location of the search algorithm.The results of Figure 2 show that the WO-RFA model is an improved classification model for estimating the risk of backfilling pipeline invalidation.

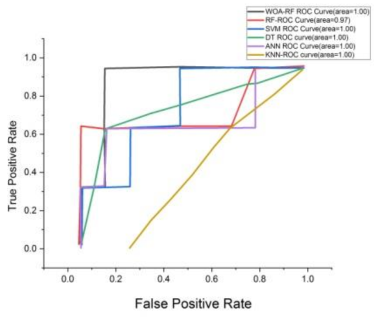

Fig.2. AUC values and ROC curves

2.4 Feature extraction using Mel Frequency Cepstral Cofficients (MFCC)

In A popular feature extraction technique for speech recognition and audio signal processing is the MFCC algorithm. It makes an effort to condense the key components of speech signals into a limited number of characteristics. The voice signal is initially pre-emphasized to amplify the high-frequency components before applying a first-order high-pass filter. Short frames, typically 20–40 milliseconds long, are separated by the pre-emphasized signal. It is usual practice to employ overlapping frames for smoother analysis. To lessen spectral leakage at boundaries, each frame is multiplied by a window function, such as the Hamming window. The framed and windowed signal is converted from the time domain to the frequency domain using an FFT. As a result, the signal is represented as a power spectrum. After that, a series of triangular filters placed along the Mel scale double the power spectrum. A perceptual scale of pitches that more accurately simulates human auditory perception is the Mel scale. To simulate how loudness is perceived by people, the logarithm of the filterbank energies is calculated. The generated MFCC features can be fed into a variety of voice recognition algorithms, including deep learning or HMMs. They offer a condensed representation of the speech signal that captures spectral and perceptual traits crucial for speech recognition tasks.

3. Result and Discussion

A method's A method's dependability and efficacy are contrasted with those of more well-known methods like Deep Neural Networks (DNN) [19] and Convolutional Neural Networks [20] to show how successful it is. WO-RFA has been suggested for use in the speech recognition system. These methods are evaluated against traditional ones using several criteria, such as accuracy, precision, recall, and cost of implementation.

Accuracy

Accuracy is the ability of a voice recognition system to correctly categorise an incident based on its overall frequency. The precision of the existing and upcoming systems is shown in Fig. 3. The proposed WO-RFA has been suggested to be used to develop a voice recognition system due to its accuracy. CNN and DNN are accurate to a degree of 84.5 and 92.7%, respectively, however the proposed technique is accurate to a degree of 98.3%. It illustrates that the suggested approach is more precise than the existing one. Accuracy values are displayed in Table 1.

$$Accuracy \rightarrow \frac{TP+TN}{TP+FP+FN+TN} \quad (9)$$

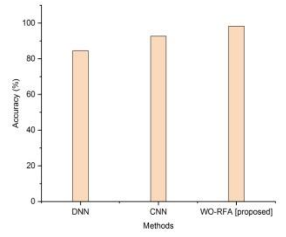

Fig.3. Accuracy for existing and proposed method

Table 1. Comparison of accuracy

Methods	Accuracy (%)
DNN	84.5
CNN	92.7
WO-RFA [proposed]	98.3

Precision

The development of a speech recognition system makes use of a classification model's capacity to concentrate only on pertinent data points. Fig. 4 displays the accuracy of the proposed and existing methods. It has been suggested that the voice recognition system use the planned WO-RFA accuracy. While CNN has a precision of 92.1% and DNN has a precision of 87.3%, the proposed method has a precision of 98.1%. It demonstrates that the proposed method is more precise than the current one. The precision values are shown in Table 2.

$$Precision \rightarrow \frac{TP}{TP+FP} \quad (10)$$

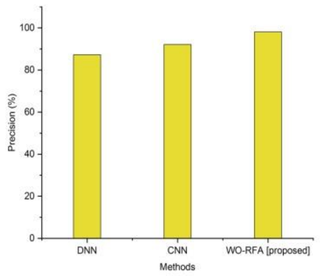

Fig.4. Precision for existing and proposed method

Table 2. Comparison of precision

Recall

The total number of true positives less the number of false negatives is used to quantitatively calculate recall. The creation of a voice recognition system can make use of a model's capacity to locate all important events in a batch of data. The planned and actual system recalls are shown in Fig. 5. The planned WO-RFA recall in the voice recognition system has been advised. The proposed approach has a 99.3% recall rate compared to CNN's 94.2% and DNN's 89.2%. It demonstrates that the suggested method has a higher recall rate than the current one. The recall values are displayed in Table 3.

$$Recall \rightarrow \frac{TP}{TP+FN} \quad (11)$$

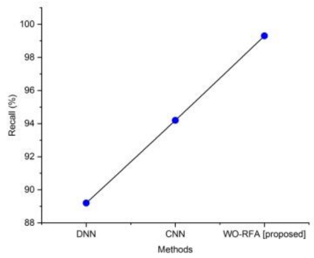

Fig.5. Recall for existing and proposed method

Table 3. Comparison of recall

Methods	Recall (%)
DNN	89.2
CNN	94.2
WO-RFA [proposed]	99.3

F1-Measure

The F1 statistic combines accuracy and recall to assess the overall efficacy of a classification model or system. It is widely used to gauge how effectively a model distinguishes and categorises speech recognition systems. The harmonic mean of recall and accuracy, which adds the two metrics to get a single result, is the F1 measure. It is calculated using the formula below:

$$F1 - Measure \rightarrow 2 * \frac{(Precision \times Recall)}{(Precision + Recall)} \quad (12)$$

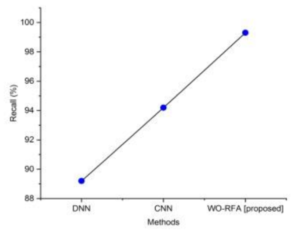

Fig.6. F1-Measure for existing and proposed method

Table 4. Comparison of f1-measure

Methods	F1 Measure (%)
DNN	86.5
CNN	89.9
WO-RFA [proposed]	97.7

Figure 6 displays the F1 metric for the proposed and existing systems. It has been suggested that the voice recognition system use the proposed WO-RFA metric. While CNN and DNN have achieved 89.9% and 86.5% of the F1 measure, respectively, the suggested system obtains 97.7%. It illustrates that the suggested technique outperforms the current one in terms of F1 measure. Table 4 displays the values for the F1-measure.

4. Conclusions

An Uzbek language voice corpus was acquired to train the proposed ASR model for this work. The modular DNN-HMM ASR and the Uzbek language's E2E ASR were then carefully compared. In order to compare the performance of the most sophisticated ASR system with that of a linguist and a native speaker, we performed an error analysis. The results of the tests revealed that the machine ASR system outperformed a native speaker by a wide margin. By using WER, which performs on average 3.5% worse than linguists in transcribing the raw Uzbek text, we also discovered a high degree of resemblance between machine errors and linguist transcription. We have created an E2E transformer for the Uzbek ASR and its dialects. There are several potential futures uses for an ASR system that employs the WO-RFA. Voice assistants like Alexa, Siri, and Google Assistant already make extensive use of ASR systems. These voice assistants can enhance their recognition and performance of spoken commands, leading to more precise and dependable responses, by implementing the WO-RFA algorithm. To translate spoken language into written text, ASR systems are frequently employed in transcription services. The WO-RFA can be included in transcriptions to dramatically improve accuracy, making them more efficient and reliable for a variety of applications, including meeting, legal, and medical transcription. Overall, the combination of the random forest algorithm and the whale optimization algorithm represents a promising step towards enhancing the precision and effectiveness of automated speech recognition systems, potentially paving the way for improvements in speech-to-text technology and its applications across a variety of fields.

Reference

[1] Rao, P.S., Parida, P., Sahu, G. and Dash, S., 2023. A multi-view human gait recognition using a hybrid whale and gray wolf optimization algorithm with a random forest classifier. *Image and Vision Computing*, p.104721.

[2] Kaur, B., Rathi, S. and Agrawal, R.K., 2022. Enhanced depression detection from speech using Quantum Whale Optimization Algorithm for feature selection. *Computers in Biology and Medicine*, *150*, p.106122.

[3] Evers, K. and Chen, S., 2022. Effects of an automatic speech recognition system with peer feedback on pronunciation instruction for adults. *Computer Assisted Language Learning*, *35*(8), pp.1869-1889.

[4] Palaz, D., Magimai-Doss, M. and Collobert, R., 2019. End-to-end acoustic modeling using convolutional neural networks for HMM-based automatic speech recognition. *Speech Communication*, *108*, pp.15-32.

[5] Li, S., Dabre, R., Lu, X., Shen, P., Kawahara, T. and Kawai, H., 2019, September. Improving Transformer-Based Speech Recognition Systems with Compressed Structure and Speech Attributes Augmentation. In *Interspeech* (pp. 4400-4404).

[6] Bhardwaj, V. and Kadyan, V., 2020, October. A deep neural network trained Punjabi children speech recognition system using the Kaldi toolkit. In 2020 IEEE 5th international conference on computing communication and Automation (ICCCA) (pp. 374-378). IEEE.

[7] Yadav, I.C., Shahnawazuddin, S. and Pradhan, G., 2019. Addressing noise and pitch sensitivity of speech recognition system through variational mode decomposition-based spectral smoothing. *Digital Signal Processing*, *86*, pp.55-64.

[8] Tanaka, T., Masumura, R., Moriya, T., Oba, T. and Aono, Y., 2019. A Joint End-to-End and DNN-HMM Hybrid Automatic Speech Recognition System with Transferring Sharable Knowledge. In *INTERSPEECH* (pp. 2210-2214).

[9] Guglani, J. and Mishra, A.N., 2021. DNN-based continuous speech recognition system of Punjabi language on Kaldi toolkit. *International Journal of Speech Technology*, *24*, pp.41-45.

[10] Chai, L., Du, J., Liu, Q.F. and Lee, C.H., 2020. A cross-entropy-guided measure (CEGM) for assessing speech recognition performance and optimizing DNN-based speech enhancement. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, *29*, pp.106-117.

[11] Wang, D., Wang, X. and Lv, S., 2019. An overview of end-to-end automatic speech recognition. *Symmetry*, *11*(8), p.1018.

[12] Abulimiti, A. and Schultz, T., 2020, May. Automatic speech recognition for Uyghur through multilingual acoustic modeling. In *Proceedings of the 12th Language Resources and Evaluation Conference* (pp. 6444-6449).

[13] Terhiija, V., Sarmah, P. and Vijaya, S., 2019. Development of Speech Corpus and Automatic Speech Recognition of Angami. *22nd Oriental-COCOSDA, Cebu, Philippines*.

[14] Tao, F. and Busso, C., 2020. End-to-end audiovisual speech recognition system with multitask learning. *IEEE Transactions on Multimedia*, *23*, pp.1-11.

[15] Abate, S.T., Tachbelie, M.Y. and Schultz, T., 2020, May. Deep neural networks based automatic speech recognition for four Ethiopian languages. In *ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)* (pp. 8274-8278). IEEE.

[16] Madhavaraj, A. and Ganesan, R.A., 2022. Data and knowledge-driven approaches for multilingual training to improve the performance of speech recognition systems of Indian languages. *arXiv preprint arXiv:2201.09494*.

[17] Park, H., Kim, C., Son, H., Seo, S. and Kim, J.H., 2022. Hybrid CTC-attention network-based end-to-end speech recognition system for the Korean language. *Journal of Web Engineering*, pp.265-284.

[18] Valizada, A., Akhundova, N. and Rustamov, S., 2021. Development of Speech Recognition Systems in Emergency Call Centers. *Symmetry*, *13*(4), p.634.

[19] Zhang, W., Cui, X., Finkler, U., Saon, G., Kayi, A., Buyuktosunoglu, A., Kingsbury, B., Kung, D. and Picheny, M., 2019. A highly efficient distributed deep learning system for automatic speech recognition. arXiv preprint arXiv:1907.05701.

[20] Guo, H., Zhou, J., Koopialipoor, M., Jahed Armaghani, D. and Tahir, M.M., 2021. Deep neural network and whale optimization algorithm to assess flyrock induced by blasting. Engineering with Computers, 37, pp.173-186.

[21] Singh, C. ., Gangwar, M. ., & Kumar, U. . (2023). Improving Accuracy of Integrated Neuro-Fuzzy Classifier with FCM based Clustering for Diagnosis of Psychiatric Disorder. International Journal on Recent and Innovation Trends in Computing and Communication, 11(2s), 244–248. https://doi.org/10.17762/ijritcc.v11i2s.6143

[22] Harris, K., Green, L., Perez, A., Fernández, C., & Pérez, C. Exploring Reinforcement Learning for Optimal Resource Allocation. Kuwait Journal of Machine Learning, 1(4). Retrieved from http://kuwaitjournals.com/index.php/kjml/article/view/155

[23] Dhabliya, D., Sharma, R. Cloud computing based mobile devices for distributed computing (2019) International Journal of Control and Automation, 12 (6 Special Issue), pp. 1-4.