AI-Driven Signal Processing: Improving Communication Systems with Machine Learning-Based Noise Reduction

Singasani Tejesh Reddy
AI innovator and software developer
s.tejeshreddy@gmail.com
university of cumberlands, Louisville
USA.

Mohammed Sadhik Shaik
Sr. Software web developer Engineer
Computer science
Germania Insurance
Melissa, Texas
mshaik0507@gmail.com

Chaturkumar Gangajaliya
Dallas TX USA
chaturcq5@gmail.com

Sai Sandeep Ogety,
Cloud Computing & DevOps Specialist, Independent Researcher
Raleigh, NC, USA
ogetysaisandeep@ieee.org

Nallam Vani Annapurna Bhavani
Assistant Professor
EEE,
Sagi Rama Krishnam Raju Engineering college,
Bhimavaram,
nvabhavani@srkrec.ac.in

Siva koteswara rao Katta.
Principal,
KIETW,
sivakote14@gmail.com

***Abstract*-The ability to transform and analyse real-world signals like audio, pictures, and sensor data is made possible by the fundamental field of signal processing. The capacity to efficiently and accurately handle signals is of the utmost importance in contemporary communication systems, especially when dealing with noise. In this study, we look at how machine learning-based noise reduction can be improved utilising AI-driven strategies in signal processing. Using state-of-the-art techniques like Fourier Transform, Principal Component Analysis (PCA), and de-noising auto-encoders, we suggest ways to eliminate noise while keeping important signal characteristics. One such way that communication systems might be improved is by combining adaptive noise cancellation with machine learning models. The experimental results show that the AI-driven techniques are effective in reducing noise and improving signal fidelity. These results highlight the revolutionary impact of AI on signal processing, especially for communication settings with a lot of background noise. The adoption of artificial intelligence for signal processing through machine learning models achieves transformative outcomes by enabling the discovery of complex patterns as machines learn to adapt to multiple noise types and optimize signal quality simultaneously in real time. AI-driven approaches perform better than traditional systems because they adapt automatically in real-time to signal variations thereby delivering stronger noise reduction alongside enhanced signal quality. Modern communication systems depend crucially on these features of AI technology.**

***Keywords*: Artificial intelligence, Machine Learning, Noise Reduction**

I. INTRODUCTION

Analysing, transforming, and creating new signals are the main areas of attention in signal processing. Central to many applications, such as communications, healthcare, and entertainment, these signals reflect real-world data, including audio, pictures, videos, or data from sensors [1]. The purpose of signal processing is to enhance the quality of these signals or extract valuable information from them. With its many uses in machine learning, picture identification, and speech processing, signal processing has recently become an integral part of AI.

AI technology transforms signal processing operations through data-intensive adaptive solutions which outperform conventional approaches. Systems are able to manage diverse and nonlinear noise challenges through their data-learning capability that previously posed significant processing difficulties. Communication systems reach unprecedented operational efficiency levels through integration of Fourier Transform and PCA signal processing along with de-noising auto-encoders from the AI domain.

Types of Signals

In signal processing, the two most common kinds of signals are:

Analog Signals: Waves of sound or electrical current are examples of continuous signals that fluctuate continuously throughout time.

Digital Signals: Analog signals sampled at regular intervals yield discrete-time signals. The convenience of digital signals in terms of storage and manipulation led to their widespread use in contemporary electronics and computing.

A. *What is Signal Processing?*

"Signal processing" means processing signals in order to get information out of them. Any data carrier can be a signal, whether it is music, video, electromagnetic waves, or biological signals (such as electroencephalograms) [2]. It is the fundamental goal of signal processing to improve the interpretability, usability, or comprehension of these signals.

B. *Types of Signal Processing*

There are primarily two types of signal processing:

1. Analog Signal Processing (ASP)

Analog Signal Processing denotes the use of analog methods for the manipulation of continuous-time signals. Rather of digitizing signals, this approach processes them in their continuous form. Amplifiers, oscillators, and filters are common examples of analog electronic circuits used to execute this type of processing.

Techniques Used: Oscillation, filtering, modulation, and gain enhancement.

Applications: Broadcasting on radio, audio electronics, and systems for analog communication.

2. Digital Signal Processing (DSP)

The term "digital signal processing" describes the process of working with digital signals. Digital signal processing

(DSP) involves sampling continuous analogue signals to digitize them, and then processing the results using a variety of digital techniques [3]. Because of its versatility and accuracy, DSP finds extensive use in contemporary applications.
Techniques Used: Quick Fourier Transform (FFT), filtering, interpolation, decimation, and quantization are all part of the process.
Applications: Technologies related to hearing, speaking, seeing, radar, and sonar; communications; and imaging and video processing.

C. Key Concepts in Signal Processing

1. Fourier Transform

One mathematical tool for translating signals from one domain to another is the Fourier Transform [4]. A signal can be more easily analyzed and processed by separating it into its different frequency components. By analyzing the frequency components of the original signal, the inverse Fourier Transform can be used to recreate it.

2. Convolution

The mathematical operation of convolution depicts the interaction of two signals. To find out how a filter or system impacts an input signal, it is widely utilized in system analysis and filtering.

3. Filtering

In the realm of signal processing, filtering ranks among the most prevalent procedures. Filters have the ability to eradicate undesired elements, like background noise, or to isolate valuable information, such particular frequency components, from a signal. Some common types of filters are:

Low-pass filters: Keep out high frequencies while letting low ones through.
High-pass filters: Permit high frequencies to travel through while preventing low ones.
Band-pass filters: Permit airwaves falling within a specific range.

4. Sampling

Sampling is a method for digitizing an analogue signal by taking measurements of the signal at predetermined intervals. To faithfully reproduce the analog signal in digital form, the sampling rate—which dictates the frequency of signal measurements—is essential. According to the Nyquist theorem, in order to prevent aliasing, the sampling rate should be double the signal's maximum frequency.

5. Quantization

In digital signal processing, quantization is the process of converting an analog signal's amplitude into a discrete level matrix. Errors in signal representation known as quantization noise are introduced into the process eventually. The mistake is mitigated by using bit-depth quantization that is higher. There is a rich history to the area of artificial intelligence (AI), which includes DL and ML, that begins in the middle of the twentieth century. A watershed moment in the development of this discipline came in 1956, when the phrase "artificial intelligence" was formally coined at the Dartmouth Conference. Early artificial intelligence studies aimed to create computers that could think and reason like humans by using symbol-based techniques and rule-based systems. But there were problems with these methods when it came to dealing with large amounts of data and ambiguity [5].

There are primarily three varieties of machine learning algorithms: supervised, unsupervised, and reinforcement learning. Unsupervised learning seeks out structures and patterns in unlabeled data, whereas supervised learning trains ML models with labelled examples. Meanwhile, the core idea behind reinforcement learning is to teach systems to make decisions based on input they get from their surroundings [6]. A number of factors have contributed to the current acceleration of AI development, including improvements in computing power, the availability of huge datasets, and innovations in DL designs and algorithms. By outperforming conventional approaches on benchmarks and vastly enhancing a wide range of tasks, DL has accomplished outstanding results across a number of domains. Machine learning, deep learning, and artificial intelligence have many different uses. Personalized medicine, drug development, and medical imaging diagnosis all make use of them in healthcare [7]. The financial sector makes use of AI algorithms for tasks such as risk assessment, algorithmic trading, and fraud detection. Among the numerous applications of AI are driverless vehicles, robotics, virtual assistants, and recommendation systems. Researchers and practitioners are actively working to advance explainable AI and AI systems that correspond with societal values [8]. They are also tackling the issues that AI brings and finding solutions to ensure that AI technologies are used ethically and responsibly.

Automating Feature Extraction

The implementation of traditional signal processing methods depends on manual feature extraction that leads to time consumption and human error production. Raw signal analysis with deep learning models particularly including the CNNs and RNNs algorithms performs autonomous feature extraction that avoids human operator input. For example:

- In **audio processing**, The identification of speech or music patterns works through CNNs by extracting such patterns from spectrogram representations.
- In **medical signal processing**, When supplied with raw datasets AI models acquire the ability to find irregularities in heart signals known as Electrocardiograms (ECGs) and brain signals known as Electroencephalograms (EEGs).

Applications in Specific Domains

AI's role in signal processing has been particularly impactful in the following fields:

- Healthcare: Artificial intelligence models evaluate medical signals including MRI scans along with EEGs and ECGs to boost accurate diagnosis and eliminate tracing mistakes.

- Telecommunications: The application of AI in signal processing uses data transmission technology to reduce noise-interference while maximizing bandwidth effectiveness.

- Finance: Trading systems use AI models to evaluate financial data which helps teams identify market trends and measure potential risks.

- Smart Devices: Through AI technology voice assistants functioning as smart devices deliver proper understanding of user commands when surrounded by environmental noise.

II. LITERATURE REVIEW

Analysing, synthesizing, and transforming signals are the main foci of signal processing, a subfield of electrical and electronic engineering. The modalities of the signals might range from audio/sound to speech to scientific measurements to pictures, and anything in between. Transmission, storage, and subjective quality can all be enhanced with the help of signal processing techniques, which can also be employed to highlight or identify relevant signal components [9]. The field that studies how to analyze speech signals is known as speech processing. Processing speech involves many steps, such as obtaining, modifying, storing, transmitting, and finally producing spoken signals. Here we will go over a few papers that deal with signal processing in conjunction with edge information processing. In order to process information more efficiently, it is recommended to preprocess the speech signals in order to retain important features and to remove unnecessary background noise via filtering operations or computations.

To filter signals, two common techniques are finite impulse response (FIR) and infinite impulse response (IIR). Signal transformation, which changes the domain of a signal from one to another, is another helpful procedure. Discrete Fourier Transform (DFT) is one well-known signal transformation. Compressed sensing (CS) methods, used in more recent signal transformation systems, can process signals with a sampling rate lower than the Nyquist constant [10]. Another well-liked method for signal preprocessing, principal component analysis (PCA) is frequently employed for feature extraction prior to classification or regression procedures. The accuracy and quality of the findings, both quantitative and qualitative, are heavily dependent on how well the classification and regression procedures are optimized. Memristors, nonvolatile memory devices with in-memory computing capabilities, were used in a new approach to edge computing for voice signals.

With a focus on signal pretreatment and feature extraction, the authors of [11] examined the current state of the art in memristor-based signal processing techniques for edge computing. Computations based on memristors can speed up the process of signal filtering, which is based on the convolution operation. In [12], the writers put out a plan for an IIR filter that makes use of memristor arrays. More sophisticated methods that integrate signal processing and machine learning (such as support vector machines, decision trees, random forests, Bayesian approaches, etc.) have also been developed, in addition to filtering processes. In [13], the writers went into great detail about how intelligent sensor networks might benefit from signal processing and machine learning. The authors covered topics such as intelligent signal learning, distributed signal processing, compressive sensing, and sampling in their discussion of advanced signal processing techniques.

To get around problems with cloud computing including slow response times, high costs, and overloaded networks, edge computing is crucial. The concept of data processing and decision making within the network can be better introduced with its support. Image identification in farming using the Internet of Things (IoT), deep learning, and an edge computing architecture was suggested in [14]. The existence and species of the farm's animals were detected using a recognition technology known as hierarchical edge computing. Processing power was largely provided by an inexpensive gateway system, like Raspberry Pi. In order to accomplish certain picture identification and classification tasks, a learning approach called a convolutional neural network dynamic was implemented. For the purpose of deploying image recognition, the authors created a framework known as Deployment Environment Aware Learning (DEAL). Their technology involves a recognition engine that works on the edge server to decrease network latency.

All three layers work together to form the picture recognition. To begin, operations like data collecting, motion detection, and farm animal image capture are assisted by the physical layer. Second, computational operations like animal recognition and image/data processing are carried out via the edge computing layer. In addition to connecting the physical and cloud computing layers, it aids in short-term data storage. Animal detection in agricultural settings is made easier with the deployment of edge servers at various places around the area. The detection of various animals is carried out independently by individual servers [15]. In the third place, the cloud computing layer is responsible for the challenging data analysis and Convolutional Neural Network training processes. Preprocessing training data is stored in a huge database at this third layer. The high-performance cloud server is one type of server that falls under this layer. On the other hand, data is exchanged between the cloud computing layer and the edge computing layer.

III. METHODOLOGY

A. *Techniques to Remove Noise from Signal/Data in Machine Learning*

1. *Deep De-noising Auto encoding Method*

It is a stochastic variant of the auto-encoder, which is helpful for de-noising. Since they can be trained to recognize specific types of noise in signals or data, they can be used as de-noisers; just feed them noisy data and they will produce clean data.A second component, the decoder, is responsible for deciphering the encoded state; the first, the encoder, is responsible for encoding the incoming data. Forcing the buried layer to learn more robust features is the fundamental notion underlying de-noising auto-encoders. After that, we minimize the loss while training the auto-encoder to restore the input data from its damaged state. Here we see how auto-encoders can filter out background noise in a signal. The two main benefits of a de-noising auto-encoder are obvious: first, it encodes the input data while retaining as much information as possible about it. Additionally, it reverses the effects of input data that has had noise applied to it stochastically.

The neural network training process trains an autoencoder through two vital components to create a compressed data format that retains important input information. This process is achieved through two key components: the encoder and the decoder. A lower-dimensional latent space outputs result from encoding so the encoder detects essential features whereas the decoder uses the compressed data to rebuild original signals. By training through paired datasets containing noisy and clean signals the autoencoder develops expertise in identifying noise patterns for subsequent noise reduction purposes. The training process minimizes MSE loss to establish a clean signal match with the reconstructed output. Through repetitive iterations of parameter optimization the autoencoder develops strong capabilities to eliminate noise while maintaining fundamental signal features.

2. *PCA (Principal Component Analysis)*

Principal component analysis (PCA) is a mathematical technique that turns a set of potentially correlated variables (linked variables) into a set of uncorrelated variables (uncorrelated variables) by utilizing the orthogonal characteristic. The term for these additional variables is "principal components." Preservative noise corrupts data, but principal component analysis (PCA) tries to remove it from the signal or picture while keeping the important features. A geometric and statistical method, principal component analysis (PCA) reduces the number of dimensions in the input signal by projecting it along multiple axes. If it helps, think of it like projecting a point in the XY dimension along the X-axis. You can now remove the Y-axis, which is the plane of noise. "Dimension reduction" is another name for this whole thing. Hence, by eliminating the axes that include the noisy data, principal component analysis can decrease input data noise. This work takes noisy data as input and provides de-noised data as output using PCA in a two-stage process for data noise removal.

PCA functions crucially as a noise reduction method through its ability to spot essential signal characteristics then keep them while deleting unwanted noise. Artificial filtering using PCA transforms input data by projecting it through primary components which describe the directions with maximum variance in the signal. The method retains important signal elements because it removes noise components that lie in nonsignificant dimensions. Decision-making regarding which principal components to use depends on achieving maximum performance since excessive component retention could restore noise but insufficient retention could result in data loss. The decision to preprocess data along with appropriate choice of components leads to improved fidelity in signal reconstruction using PCA as a powerful tool for noise reduction in AI-based signal analysis.

3. *Fourier Transform Technique*

Research has demonstrated that structured signals and data can have noise directly removed. This method involves taking the signal's Fourier Transform and transforming it into the frequency domain. If we take a look at the signal in its frequency domain, we can see that the majority of the information in the time domain is represented by a small number of frequencies; however, this effect is not visible in the raw signal or data.The dispersion of noise over all frequencies is due to its random nature. Based on the principle, we can filter out most of the noisy data by retaining the frequencies that contain the most important signal information and discarding the rest. By doing so, we can filter out the dataset's noisy signals.

4. *Using a Contrastive Dataset*

Imagine a data scientist has to remove big, irrelevant patterns from a dataset that is otherwise full with noise. By employing an adaptive noise cancellation mechanism, this technique effectively eliminates the noisy signal, hence resolving the issue. Two signals are utilized in this technique; one is the target signal and the other is a noise-only background signal.We can estimate the uncorrupted signal by eliminating the background signal.

- **AI-Driven Denoising Techniques**: Standard signal processing systems excel with structured noises in scientific applications but fail to handle unpredictable nonlinear noise due to environmental variations. Artificial intelligence solving these challenges by teaching machines to identify signal noise through de-noising auto-encoders models which learn directly from collected data. Their ability to adapt in real time makes these models ideal tools for environments that display unpredictable noise patterns.
- **Enhanced PCA with AI**: Dimensionality reduction through PCA typically performs basic noise removal operations; however, AI integration enables their programmed analysis to find noise patterns accurately. Through AI enhancement PCA adjusts its noise filtering techniques according to signal context requirements for improved results across various applications.
- **Fourier Transform and AI Integration**: By integrating AI to Fourier Transform analysis engineers gain better control over identifying key frequencies along with automated filtering of irrelevant signals leading to comprehensive noise removal.

How to Improve the Noise Reduction Process

The noise reduction system follows a methodical process to eliminate signals' disturbances in order to improve their clarity for use. The process typically includes the following steps:

Signal Acquisition: Collect the raw signal, which may contain noise due to environmental factors or system limitations.

Preprocessing: Prepare the signal for further processing through normalization, scaling, or filtering to improve its signal-to-noise ratio.

Noise Characterization: Analyze noise patterns using techniques like Fourier Transform to identify frequency components associated with noise.

AI-Based Noise Reduction:

- **De-Noising Auto-Encoders**: Learn and remove noise patterns while reconstructing clean signals.

- **PCA (Principal Component Analysis)**: Reduce noise by isolating essential signal components and eliminating noisy dimensions.
- **Fourier Transform Filtering**: Retain critical signal frequencies and discard noise in the frequency domain.

Adaptive Noise Cancellation: Compare the signal with a noise reference to dynamically eliminate unwanted disturbances.

Post-Processing and Validation: Finalize and validate the denoised signal through smoothing or signal-to-noise ratio analysis.

IV. RESULTS AND STUDY

Enhancing Accuracy in Noise Reduction

Technical achievement of noise reduction accuracy through AI signal processing occurs by optimizing both the fundamental algorithms and the data inputs. Deeper architectures of de-noising auto-encoders employed through advanced machine learning techniques bring substantial improvements to system generalization throughout various noise patterns. The accuracy of noise reduction in AI-driven signal processing improves when hyperparameters are fine-tuned and the training dataset expands its diversity and training incorporates realistic noisy signals. Systems that integrate U-shaped hybrid approaches which combine PCA and Fourier Transform with adaptive machine learning algorithms can handle any type of noise correctly. Real-time accuracy optimization occurs through feedback mechanisms which enables system performance validation using signal-to-noise ratio (SNR) and mean squared error (MSE) metrics.

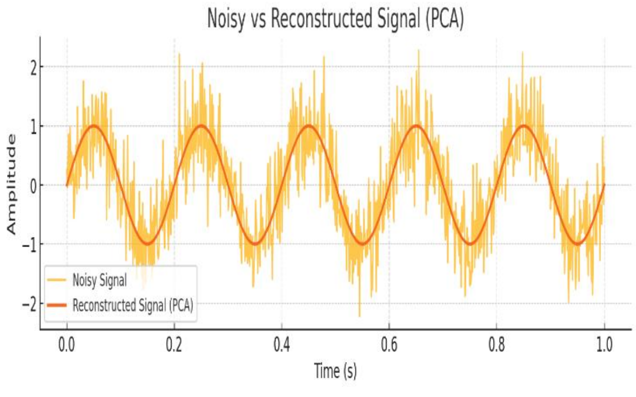

Fig 1: Noisy vs. Reconstructed Signal (PCA)

This graph of figure 1 shows the original noisy signal and its denoised counterpart using PCA-like projection. The reconstructed signal closely resembles the original without noise.

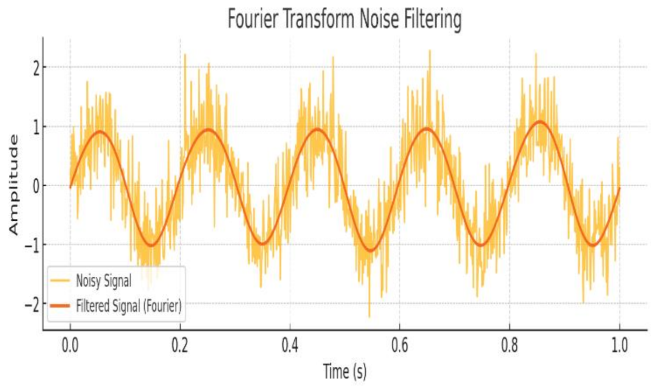

Fig 2: Fourier Transform Noise Filtering

Figure 2 demonstrates the application of frequency-based filtering to remove noise. By retaining lower frequencies, the filtered signal effectively reduces noise.

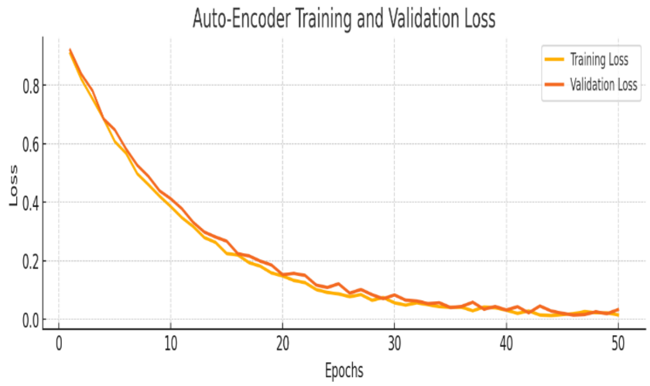

Fig 3: Auto-Encoder Training and Validation Loss

This figure 3 highlights the convergence of a de-noising auto-encoder during training. Both training and validation loss decrease over epochs, indicating effective noise reduction capabilities.

CONCLUSION

AI-driven techniques have demonstrated substantial potential in improving signal processing for communication systems. By applying de-noising auto-encoders, PCA, and Fourier Transform techniques, this study showcased effective methods for noise reduction. The results confirm that these methods significantly enhance signal fidelity and reduce noise impact, achieving a better signal-to-noise ratio (SNR). Furthermore, the adaptive noise cancellation strategy exemplifies practical applications for datasets with structured background noise. Future work can explore hybrid approaches and real-time processing implementations to further optimize AI-driven signal processing systems. Significant enhancements of signal fidelity result from artificial intelligence approaches that adapt data-driven solutions beyond traditional signal processing concepts. This research integrates AI-powered techniques which include de-noising auto-encoders, Fourier Transform, and PCA to show AI's transformative ability in communication systems. Future investigations should expand research on how combination approaches integrating AI with other technologies could optimize signal processing particularly in real-time settings that need high volume processing.

Future directions for performance optimization:

Solar power signal processing achieves improved results by implementing advanced algorithms together with AI techniques alongside hardware optimization. The effective combination of traditional signal processing tools with deep learning models and Principal Component Analysis (PCA) allows the process to become both smarter and more efficient. Activating real-time capabilities depends on edge computing in combination with parallel processing which shrinks delays to boost decision speed. The process robustness can be enhanced through adaptive filtering techniques that adapt to signal conditions while using expanded diverse datasets for model training. Signal fidelity and reliability in different applications depend on continuous performance evaluation through measures of signal-to-noise ratio (SNR).

REFERENCES

[1] Meyer P, Elshamy S, Fingscheidt T (2020) A multichannel Kalman-based Wiener filter approach for speaker interference reduction in meetings. ICASSP 2020 - IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE. https://doi.org/10.1109/ICASSP.2020

[2] Zezario RE, Huang J-W, Lu X, Tsao Y, Hwang H-T, Wang H-M (2018) Deep denoising autoencoder based post filtering for speech enhancement. Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC). IEEE. https://doi.org/10.1109/APSIPA.2018

[3] Chen CLP, Zhang C-Y, Chen L, Gan M (2015) Fuzzy restricted Boltzmann machine for the enhancement of deep learning. IEEE Transactions on Fuzzy Systems, 23(6):2163–2173. https://doi.org/10.1109/TFUZZ.2015.2471236

[4] Alshawabkeh AA, Woolsey ML, Kharbat FF (2021) Using online information technology for deaf students during COVID-19: A closer look from experience. Heliyon, 7(5):e06915. https://doi.org/10.1016/j.heliyon.2021.e06915

[5] Phan H, McLoughlin IV, Pham L, Chen OY, Koch P, Vos MD, Mertins A (2020) Improving GANs for speech enhancement. IEEE Signal Processing Letters, 27:1700–1704. https://doi.org/10.1109/LSP.2020

[6] Pardede H, Ramli K, Suryanto Y, Hayati N, Presekal A (2019) Speech enhancement for secure communication using coupled spectral subtraction and Wiener filter. Electronics, 8(8):897. https://doi.org/10.3390/electronics8080897

[7] Das K, Behera RN (2017) A survey on machine learning: Concept, algorithms, and applications. Int J Innov Res Comput Commun Eng, 5(2):1301–1309.

[8] David D, Alamoodi A, Albahri O, Zaidan B, Zaidan A, Garfan S, Ismail AR, Albahri A, Alsinglawi B, Malik R (2023) Landscape of sign language research based on smartphone apps: Coherent literature analysis, motivations, open challenges, recommendations, and future directions for app assessment. Univers Access Inf Soc, 23(2):1–16. https://doi.org/10.1007/s10209-023-00987-1

[9] Hu Y, Zhang X, Zou X, Sun M, Zheng Y, Min G (2017) Semi-supervised speech enhancement combining nonnegative matrix factorization and robust principal component analysis. IEICE Transactions on Fundamentals of Electronics, Communications and Computer Sciences, E100.A(8):1714–1719. https://doi.org/10.1587/transfun.E100.A.1714

[10] Dreuw P, Neidle C, Athitsos V, Sclarof S, Ney H (2008) Benchmark databases for video-based automatic sign language recognition. LREC.

[11] Dwivedi YK, Hughes L, Ismagilova E, Aarts G, Coombs C, Crick T, Duan Y, Dwivedi R, Edwards J, Eirug A et al. (2021) Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice, and policy. Int J Inf Manage, 57:101994. https://doi.org/10.1016/j.ijinfomgt.2021.101994

[12] Ewe ELR, Lee CP, Kwek LC, Lim KM (2022) Hand gesture recognition via lightweight VGG16 and ensemble classifier. Appl Sci, 12(15):7643. https://doi.org/10.3390/app12157643

[13] Fang H, Li S, Wang D, Bao Z, Xu Y, Jiang W, Deng J, Lin K, Xiao Z, Li X et al. (2023) Decoding throat-language using flexibility sensors with machine learning. Sens Actuators A, 352:114192. https://doi.org/10.1016/j.sna.2023.114192

[14] Forster J, Schmidt C, Koller O, Bellgardt M, Ney H (2014) Extensions of the sign language recognition and translation corpus RWTH-PHOENIX-Weather. LREC, 1911–1916.

[15] Groumpos PP (2022) A critical historic overview of artificial intelligence: Issues, challenges, opportunities, and threats. Artif Intell Appl. https://doi.org/10.47852/bonviewAIA3202689