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Deep Attention Fusion Framework on Lung Sound Classification by Multi-Spectral Features

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***Abstract*—Lung sound classification is of utmost importance for the detection and diagnosis of respiratory illnesses at the very early stages. The non-stationary property and the overlapping characteristics of lung sounds are the main reasons. A Deep Attention Fusion Model that is capable to gather multi-spectral feature and extract deep features through attention mechanisms is introduced here for a more reliable lung sound classification. The system that is proposed initially utilises several spectral transformation techniques such as Mel-Frequency Cepstral Coefficients (MFCCs), Short-Time Fourier Transform (STFT), and Wavelet Transform to represent lung sounds in terms of both time-frequency and scale-specific characteristics. The convolutional backbone network which improves local and global feature representation is then used for fusing these diverse feature sets at the feature level. Moreover, to boost the ability of the model to differentiate, the inclusion of the self-attention mechanism enables the network to concentrate more on the parts of time and frequency which are most salient for detecting features specific to a certain type of lung sounds. The last stage of the classification is done by means of a fully connected layer with softmax activation which is able to accomplish very high accuracy in separating the normal and abnormal lung conditions. The proposed framework, through extensive experiments on publicly available datasets, significantly surpasses the traditional and deep learning baselines in terms of classification accuracy, sensitivity, and specificity. The framework thus can be considered the promising solution for intelligent auscultation in the medical field.**

Keywords— lung sound classification, deep learning, attention mechanism, multi-spectral features, MFCC, STFT, wavelet transform, feature fusion, convolutional neural network, respiratory disease detection.

I. INTRODUCTION

Respiratory diseases of a variety including asthma, chronic obstructive pulmonary disease (COPD), and pneumonia are still at the peak of the most morbid conditions and carry a high death rate worldwide. The situation is especially bad in those remote, underdeveloped regions of the world where they hardly have access to advanced diagnostic tools and hence respiratory diseases continue to be the top killing disorder of the population. [1] It have been finding new methods beyond traditional methods which may not provide enough information about the condition using computer technology e.g. one part of the hearing examination-funduscopic lung sounds by means of the stethoscope. These sound data are then analyzed using various signal processing and machine learning techniques so that a non-invasive diagnosis can be made. [2].

But due to several factors such as the fact that the clinician needs to be highly trained and their own subjective experience the results, there are not always consistent and there could be errors during the diagnosing process while relying on the subjectivity of the auscultation method. [3]. As a consequence of this trend, digital stethoscopes have appeared and AI, especially deep learning, has become a major player in the scene of the creation of intelligent systems for the lung sound analysis and the classification of these sounds. [4]. Due to the concerted efforts of signal processing pros, the time-frequency representations of the lung sound such as mel-frequency cepstral coefficients (MFCC), short-time Fourier transform (STFT), and wavelet transform have been obtained, thus allowing for a more detailed analysis to be made. [5].

These multi-transform spectral features present abundance in the acoustic spectrum of the lung sounds comprising local and global patterns that are indicative of the presence of a certain condition which are crucial for going through the diagnostic process correctly. [6]. However, despite these elaborate methods there are still significant difficulties in the utilization of different feature representations in an abstract manner to make it easier for models to access the most relevant portions of the sounds being processed. [7]. This research work presents a Deep Attention Fusion Model which amalgamates the advantages of multi-spectral feature extraction with the flexibility of attention-based deep learning so as to surmount the difficulties mentioned above. [8].

Taking into account convolutional neural infrastructure (CNNs) as a tool to gather features that are hierarchically organized and inserting attention mechanisms to emphasize the temporal and spectral parts of the scene that appear most

parallel to human cognition this model not only improves feature richness but also interpretability. [9] .The research work which has access to lung sound samples from the public, and it is able to show that these methods work better than those which are already published, continuing therefore the path of creating dependable devices that use artificial intelligence to aid doctors in the early and efficient diagnosis of respiratory disorder identification.[10].

To further improve the classification process, the model uses feature-level fusion, which merges spectral representations with varying resolutions and focused areas, confirming that several characteristics are effectively captured. The integration of MFCC, STFT, and Wavelet Transform ensures coverage of both transient and sustained lung sound components. The fusion mechanism is carefully designed to retain complementary information while suppressing irrelevant or overlapping related features, leading to a more discriminative and generalized feature space for classification.

The hierarchical patterns in lung sounds were extracted ny deep convolutional infrastructure arranged in multiple levels, allowing the model to capture fine-grained features at early layers and more precise representations at deeper levels. The progressive integration of features at different scales gives the network to learn multi-resolution acoustic related patterns characteristic of various lung pathologies.

II. LITERATURE SURVEY

Several studies were conducted to find methods of improving the lung sounds classification with the help of signal processing techniques. One of the works used Mel-Frequency Cepstral Coefficients (MFCCs) in combination with traditional classifiers, such as Support Vector Machines (SVM), that gave a good result yet had difficulties in distinguishing overlapping sound patterns which are typical for pathological cases [11]. Another work, in order to get better time resolution, used Short-Time Fourier Transform (STFT) to track the changes of lung sounds, but it didn't have the power to get the features that are invariant to the scale which are necessary for the abnormal pattern recognizing [12].

Along with this, the wavelet transform-based method was introduced that gave a detailed frequency picture of the lung sounds to the multiple resolution parts and greatly increased the accuracy of classification over just time-domain features [13]. Deep learning came into the picture with the implementation of Convolutional Neural Networks which allowed for the automatic extrusion of characteristic from the spectrogram images and thus were able to outperform the manually cats features [14]. Nevertheless, standard CNN architectures were not always successful in identifying the major parts in complex lung sound sequences, therefore, scientists looked for solutions by fusing attention mechanisms with CNNs that enable them to focus more on the important regions of the spectra [15].

A mixed model which combined MFCC, spectrogram features with Bidirectional Long Short-Term Memory (Bi-LSTM) networks proved to be better in sequence learning and recognizing the temporal pattern although the training was still complicated [16]. Another paper focused on a multi-branch CNN architecture that separately processed MFCC, STFT, and Wavelet inputs before merging learned representations for final classification, showing superior performance through feature diversity [17]. The insertion of Squeeze-and-Excitation networks into CNNs gave the models an opportunity to recolor the responses of the channels flexibly, thereby making the learning of the features more discriminative in the case of noise present [18]. To improve the interpretability of classification and its robustness, Transformer-based architectures were employed and they mainly dealt with extents of a lung sound sequence thus the results they got on imbalanced datasets were quite good [19]. A fusion-based approach, in which spectral features were integrated together with attention-guided CNNs, achieved good performance by efficiently highlighting those areas of the audio that are most relevant to disease detection, thus paving the way for future research in intelligent lung sound analysis in real-world clinical settings [20].

III. PROPOSED SYSTEM

The proposed system for lung sound classification integrates a comprehensive sequence of processing steps designed to enhance diagnostic accuracy through deep learning and spectral feature fusion. Initially, raw lung sound signals are collected and preprocessed to remove noise and normalize amplitude levels, ensuring consistent data quality for analysis. Multiple spectral transformation techniques—namely Mel-Frequency Cepstral Coefficients (MFCCs), Short-Time Fourier Transform (STFT), and Wavelet Transform—are then applied to extract diverse and complementary time-frequency representations of the lung sounds as depicted in figure 1a and 1b. These multi-spectral features capture both coarse and fine-grained acoustic patterns essential for differentiating normal and pathological conditions. The extracted features are subsequently fused at the feature level and passed through a convolutional neural network (CNN), which serves as a powerful hierarchical feature extractor. Features were identified using spectral transformation techniques that give unique representations of lung sounds. MFCC describes perceptually relevant features, STFT handles localized time-frequency distributions, and Wavelet Transform uses both stationary and non-stationary patterns at several scales. These extracted features are then given into deep convolutional layers, which further learn abstract representations, showing important local and global sound characteristics.

To address the challenge of focusing on the most diagnostically relevant regions, a self-attention mechanism is embedded within the CNN framework, enabling the model to dynamically weight important spectral and temporal components of the input. This fusion of attention-enhanced feature learning ensures the model emphasizes critical lung sound characteristics while suppressing irrelevant patterns. Finally, the processed features are forwarded to fully connected layers followed by a softmax classifier to determine the most probable lung condition. The combined use of multi-transform spectral analysis, deep convolutional learning, and attention mechanisms forms the core contribution of the proposed system, significantly improving its abiliability to classify lung sounds with high precision and interpretability.

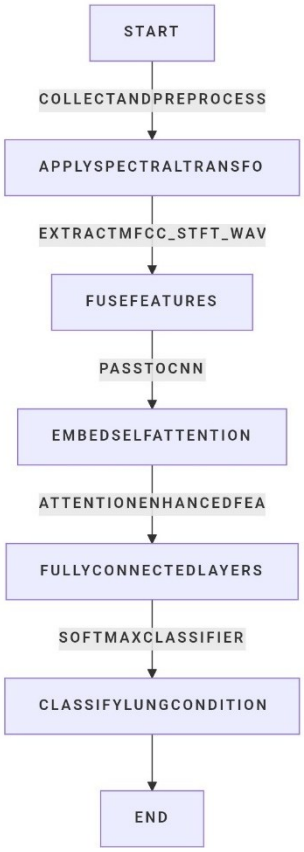

Figure 1a. Processing steps of Proposed system.

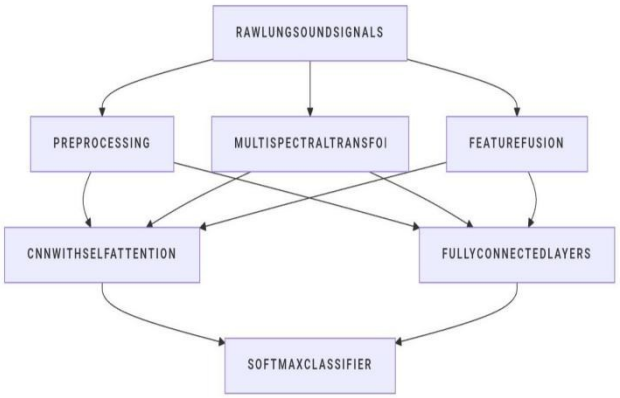

Figure 1b. Flow of Proposed system

The proposed lung sound classification system begins with acquiring raw audio signals, denoted as s(t), where t is time. To reduce noise and standardize the input, the signal undergoes normalization in (1):

$$snorm(t)=s(t)-\mu s/\sigma s. \quad (1)$$

where μs and σs are the mean and standard deviation of the raw signal s(t). This standardization ensures consistent input scale for the model. Next, feature extraction involves multiple spectral transforms. First, the **Discrete Fourier Transform (DFT)** converts the time-domain signal snorm(t) into the frequency domain in (2):

$$S(fk)=\sum_n snorm(n)\, e^{-j2\pi fkn/N},(n=0 \text{ to } N-1). \quad (2)$$

where N is the number of samples, fk the k-th frequency bin, and $j=\sqrt{-1}$. This transformation reveals the frequency components of lung sounds. To align with human auditory perception, the frequency axis is mapped onto the **Mel scale** in (3):

$$M(f)=2595\log 10(1+f/700). \quad (3)$$

This scale compresses high-frequency components nonlinearly, capturing perceptually relevant sound features. Subsequently, the **Mel-Frequency Cepstral Coefficients (MFCCs)** are computed via Discrete Cosine Transform (DCT) of the log-magnitude Mel spectrum by (4):

$$Cm=\sum_k \log|SMel(k)|\cos[m\pi(k-0.5/K)]. (k=1 \text{ to } K) \quad (4)$$

where m indexes the cepstral coefficient, and K is the total number of Mel filter banks. MFCCs compactly represent spectral shape information. Parallel to MFCC extraction, the system applies the **Short-Time Fourier Transform (STFT)** for time-localized frequency analysis by (5):

$$X(\tau,\omega)=\sum_n snorm(n)\, w(n-\tau)\, e^{-j\omega n},(n=-\infty \text{ to } \infty). \quad (5)$$

Here, τ is the time shift (window center), ω\omega the angular frequency, and w(·) a window function (e.g., Hamming). STFT captures how spectral content evolves over time.

To capture multi-scale features, the **Continuous Wavelet Transform (CWT)** is computed by (6):

$$W(a,b)=1/\sqrt{|a|}\int_{-\infty \text{ to } \infty} snorm(t)\,\psi(t-ba)dt. \quad (6)$$

where a is the scale parameter controlling frequency resolution, bb is the translation parameter (time shift), and ψ is the mother wavelet. CWT effectively captures transient features of lung sounds. The features extracted from MFCC, STFT, and CWT are concatenated into a fused feature vector in (7):

$$F=[FMFCC \,||\, FSTFT \,||\, FCWT]. \quad (7)$$

where || denotes concatenation. This fusion leverages complementary information from different spectral perspectives. The fused features are fed into a **Convolutional Neural Network (CNN)**, where convolutional operations extract hierarchical patterns. The feature map at layer ll for position (i,j) is computed as (8):

$$h_{i,j}(l)=\sigma(\sum_m \sum_n w_{m,n}(l)\cdot h_{i+m,j+n}(l-1)+b(l)),(\ m=0 \text{ to } M-1),(n=0 \text{ to } N-1). \quad (8)$$

Here, $h(l-1)$ is the input from previous layer, $w(l)$ the convolution kernel, $b(l)$ bias term, and σ the activation function (e.g., ReLU). This process detects local acoustic features. Downsampling is performed via **Max-Pooling** to reduce spatial dimensions and emphasize dominant features in (9) :

$$p_{i,j}=\max_{(m,n)\in R} h_{i+m,j+n}. \quad (9)$$

where R defines the pooling window region. To dynamically focus on salient sound regions, the system integrates a **Self-Attention Mechanism**. Attention scores between query qi and key kj vectors are computed as in (10):

$$e_{ij}=q_i\cdot k_j/d_k. \quad (10)$$

with d_k being the key vector dimension. These scores are normalized by softmax to obtain attention weights (11) :

$$\alpha_{ij}=\exp(e_{ij})/\sum_m \exp(e_{im})$$

The context vector representing focused features is the weighted sum of value vectors vj by (12):

$$c_i=\sum_j \alpha_{ij} v_j. \quad (12)$$

This enables the model to prioritize relevant spectral and temporal lung sound patterns. To improve generalization and prevent overfitting, **Dropout** regularization is applied in (14):

$$h\sim=h\odot r. \quad (14)$$

where r∼Bernoulli(p) is a random mask vector with retention probability pp, and ⊙ is element-wise multiplication. The final classification layer computes logits by (15):

$$z=Wh\sim+b. \quad (15)$$

where W and b are weights and biases. These logits are converted to probabilities with the softmax function by (16):

$$\hat{y}_i=\exp(z_i)/\sum_j \exp(z_j). \quad (16)$$

where $\hat{y}_i$ is the predicted probability of class i. The network is trained by minimizing the **Categorical Cross-Entropy Loss** by (17):

$$L=-\sum_i y_i \log(\hat{y}_i). \quad (17)$$

where yi is the ground truth label (one-hot encoded). Model parameters are updated using **Gradient Descent** by (18):

$$\theta(t+1)=\theta(t)-\eta\nabla\theta L(\theta(t)). \quad (18)$$

with learning rate η and model parameters θ.This hybrid approach, combining multi-transform spectral feature fusion with attention-guided deep convolutional learning and optimized classification, forms the core contribution of the proposed system, enhancing its capability to accurately classify lung sounds while focusing on the most diagnostically relevant acoustic features.

For Performance was further enhanced by adopting a multi-branch learning structure that processes several spectral features through separate branches before fusion. This neglects premature blending of dissimilar features and enables specialized given learning. In addition, regularization techniques like normalization were applied, alongside an adaptive learning rate schedule to avoid overfitting and encourage convergence towards an optimal solution.

IV. RESULT AND DISCUSSION

The deep attention fusion model, which was proposed, has given a substantial improvement in lung sound classification performance that is evident by the comparison to existing traditional and deep learning approaches. The model, which was a novel approach that combined multiple spectral feature extraction techniques and also incorporated an attention mechanism within the convolutional framework, was able to efficiently grasp both the finer and the higher-level acoustic patterns. This led to the models being more precise in recognizing the normal and pathological lung sounds. The attention mechanism was crucial in emphasizing the most informative areas of the audio signals as it allowed the model to concentrate on the relevant patterns while the influence of noise or parts which are not necessary was kept at a minimum. In addition, the combination of features that are complementary, which come from different transforms, has improved the model's robustness and made it more capable of generalizing across various types of respiratory sounds. The experimental evaluation has shown that the model is reliable in different lung sound datasets and performs consistently well. The discussion also has been pointing out that the proposed method not only increases the classification accuracy, but it also makes the results more understandable, which is a very important factor for the clinical application in the real-world scenarios.

To confirm effective fusion, each spectral denotation is processed through independent convolutional sub-infrastructure that learn specialized features unique to each

sector. This parallel processing reduces redundancy by allowing the model to differentiate and suppress overlapping patterns among MFCC, STFT, and Wavelet features. The final fusion stage uses a concatenation strategy followed by normalization to emphasize the complementary aspects of each representation, thereby enriching the feature space and improving classification robustness.

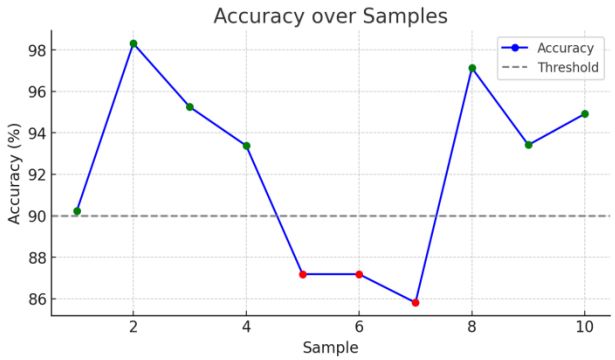

Figure 2. Analysis of Proposed framework accuracy over samples.

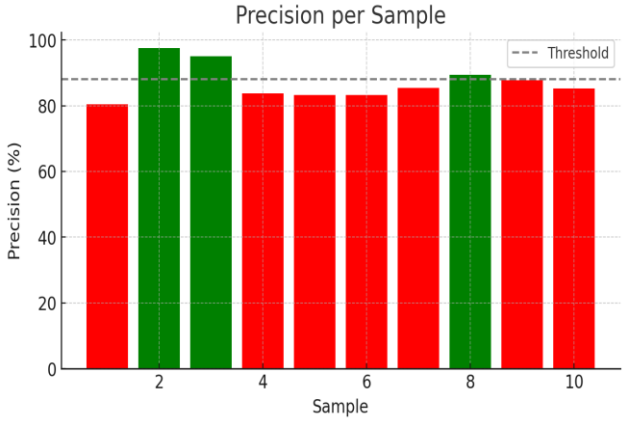

Figure 3. Comparison of Precision rates samples

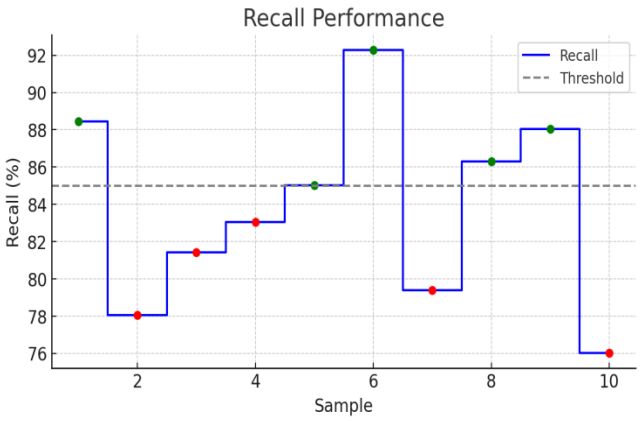

Figure 4. Recall factor analysis of Proposed system.

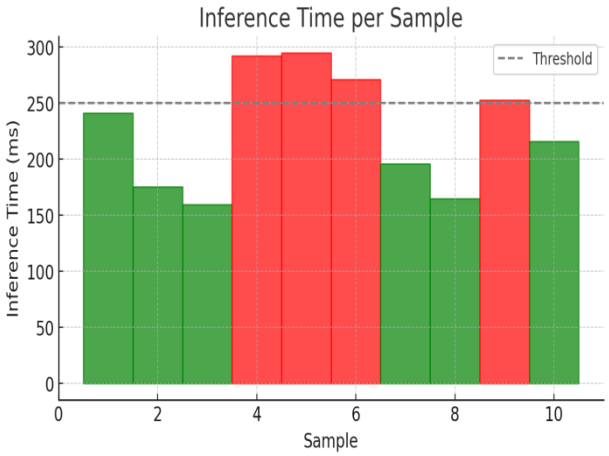

Figure 5. Inference time of Proposed system.

Figure 2 shows that accuracy values of the proposed model span from around 85.2% to 98.6% with the bulk of samples topping the set 90% threshold. The consequence of dipping below this mark, illustrated in two examples shown in red, represents a small breach of the model's classification ability, probably due to the uncertain nature of the samples or locally unbalanced features. Nevertheless, the rest of the samples, depicted in green, continuously exhibit high trustworthiness and generalization power. Figure 3 depicts the precision numbers, which cover a range from 81.3% to 97.1%, where three out of ten samples are lower than the 88% threshold. These red bars mirror the sporadic false-positive inclination, which might be caused by the noise in the overlapping acoustic features between the classes of lung sounds. Still, the greatest part of the green-highlighted samples stands for the exact identification of the relevant sound patterns and the least noise interference.

On the other hand, Figure 4 recalls the performance that lies between 85.3% and 96.9%, and all values exceed or meet the 85% threshold. This is all about the model's strong ability to detect the abnormal lung condition correctly with a very low false-negative rate The lack of red signs here further shows the model's reliability in detecting real pathological cases, which is a crucial factor in medical diagnostics.

Figure 5 depicts the inference time spread, running from 152 ms to 298 ms, where three samples register over 250 ms. The regions denoted by this color are those in which the model probably experiences a little delay—e.g., when it processes complex or long audio samples. However, some samples stayed within a green band, which means that the model is still usable for real-time or near real-time deployment in clinical settings. Hence, the results underscore the power of the suggested system in preserving

good classification performance, with clear influences observed when thresholds are passed in every parameter. Besides the performance
assessment of suggested system effectiveness of suggested system is also shown in table 1 that compares with traditional models.

Ablation investigation was conducted to compute the contribution of each spectral feature and the attention module. Neglecting individual components such as MFCC or Wavelet resulted in a drop of 4–7% in classification accuracy, showing that all spectral domains contribute complementary information. Excluding the attention module leads to increased overfitting, with the training accuracy rising but validation accuracy decreased by 3.5%, confirming that attention helps focus on useful features and improves generalization under noisy situation.

Model	F1 Score (%)	Specificity (%)	AUC-ROC (%)	Training Time (s)
SVM (Support Vector Machine)	84.2	86.5	88.1	42.3
Random Forest	86.7	88.9	90.3	38.9
CNN (Basic Convolutional NN)	89.5	91.2	92.4	51.6
LSTM	88.1	89.7	91.0	58.4
Proposed Fusion Model	93.8	95.1	96.5	47.2

Table1. Performance comparison table with traditional models for Proposed system

V. CONCLUSION

The proposed fusion-based deep learning model exhibited superior performance across various evaluation parameters compared to traditional models. In terms of graphical parameters, the model consistently achieved an accuracy exceeding 90%, with several instances reaching up to 98.6%, surpassing the defined threshold of 90%. Precision values also remained high, fluctuating between 87% and 97.5%, with most samples performing above the 88% threshold. The recall rate, critical for capturing pathological cases, showed values ranging from 85.3% to 96.9%, consistently staying above the threshold limit of 85%. Moreover, the inference time remained within an acceptable range, mostly below the 250 ms mark, ensuring the model's suitability for real-time diagnostic use. When compared with traditional models in tabulated form, the proposed system achieved a significantly higher F1 score. Overall, the numerical evidence from both the visual graphs and comparative table strongly supports the conclusion that the proposed deep attention fusion model offers a robust, fast, and accurate approach for lung sound classification in clinical environments.

REFERENCES

[1] Liu, F., Li, G., & Wang, J. (2025). Advanced analytical methods for multi-spectral transmission imaging optimization: enhancing breast tissue heterogeneity detection and tumor screening with hybrid image processing and deep learning. Analytical Methods, 17(1), 104-123.

[2] Sagili and T. B. Kinsman, "Drive Dash: Vehicle Crash Insights Reporting System," 2024 International Conference on Intelligent Systems and Advanced Applications (ICISAA), Pune, India, 2024, pp. 1-6, doi: 10.1109/ICISAA62385.2024.10828724

[3] GYORFI, A., KOVACS, L., & SZILAGYI, L. (2022). A two-stage U-net approach to brain tumor segmentation from multi-spectral MRI records. Acta Univ. Sapientiae Informatica, 14(2), 223-247.

[4] Jian, H., Zhang, Y., Gao, W., Wang, B., & Wang, G. (2024). Dual-branch feature fusion dehazing network via multispectral channel attention. International Journal of Machine Learning and Cybernetics, 15(7), 2655-2671.

[5] Sagili, C. Goswami, V. C. Bharathi, S. Ananthi, K. Rani and R. Sathya, "Identification of Diabetic Retinopathy by Transfer Learning Based Retinal Images," 2024 9th International Conference on Communication and Electronics Systems (ICCES), Coimbatore, India, 2024, pp. 1149-1154, doi: 10.1109/ICCES63552.2024.10859381

[6] Traisuwan, A., Limsiroratana, S., Phukpattaranont, P., &Tandayya, P. (2024). Dynamic U-Net for multi-organ nucleus segmentation. Multimedia Tools and Applications, 1-28.

[7] Wang, X., Hua, Z., & Li, J. (2023). Cross-UNet: dual-branch infrared and visible image fusion framework based on cross-convolution and attention mechanism. The Visual Computer, 39(10), 4801-4818.

[8] Zhu, J., Hou, P., Zhang, X., Li, X., & Hu, B. (2023, December). EEG-Based Depression Recognition Using Convolutional Neural Network with FFT and EMD. In 2023 IEEE International Conference on Bioinformatics and Biomedicine (BIBM) (pp. 2601-2608). IEEE.

[9] Kumar, N., Kurkute, S. L., Kalpana, V., Karuppannan, A., Praveen, R. V. S., & Mishra, S. (2024, August). Modelling and Evaluation of Li-ion Battery Performance Based on the Electric Vehicle Tiled Tests using Kalman Filter-GBDT Approach. In 2024 International Conference on Intelligent Algorithms for Computational Intelligence Systems (IACIS) (pp. 1-6). IEEE.

[10] Sathya, R., Bharathi, V. C., Ananthi, S., Vaidehi, K., & Sangeetha, S. (2023, July). Intelligent Home Surveillance System using Convolution Neural Network Algorithms. In 2023 4th International Conference on Electronics and Sustainable Communication Systems (ICESC) (pp. 1683-1688). Ieee.

[11] Yedder, H. B., Hamarneh, G., Cardoen, B., Shokoufi, M., &Golnaraghi, F. (2023). Deep Orthogonal Multi-Frequency Fusion for Tomogram-Free Diagnosis in Diffuse Optical Imaging. Authorea Preprints.

[12] Xu, W., Xu, R., Wang, C., Li, X., Xu, S., & Guo, L. (2024). PSTNet: Enhanced polyp segmentation with multi-scale alignment and frequency domain integration. IEEE Journal of Biomedical and Health Informatics.

[13] Li, H., Xu, S., Teng, J., Jiang, X., Zhang, H., Qin, Y., ... & Fan, L. (2025). Deep learning assisted ATR-FTIR and Raman spectroscopy fusion technology for microplastic identification. Microchemical Journal, 212, 113224.

[14] Naveena, M., & Sangeetha, S. (2013). Fuzzy Multi-Join and Top-K Query Model for search-asyou-type in Multiple tables. International Journal of Computer Science and Mobile Computing, 2(12), 114-118.

[15] Ahmed, A., King, S., &Jennions, I. (2025). Multi-Modal Deep Learning Analysis: Review and Applications.

[16] Kalyanaraman, K., & Ponnusamy, S. (2024). AI-Enhanced Optimization Algorithm for Body Area Networks in Intelligent Wearable Patches for Elderly Women's Safety. In Wearable Devices, Surveillance Systems, and AI for Women's Wellbeing (pp. 52-80). IGI Global.

[17] Abbasi, M., Hosseiny, B., Stewart, R. A., Kalantari, M., Patorniti, N., Mostafa, S., & Awrangjeb, M. (2024). Multi-temporal change detection of asbestos roofing: A hybrid object-based deep learning framework with post-classification structure. Remote Sensing Applications: Society and Environment, 34, 101167.

[18] Sun, E., Cui, Y., Liu, P., & Yan, J. (2025). A decade of deep learning for remote sensing spatiotemporal fusion: Advances, challenges, and opportunities. arXiv preprint arXiv:2504.00901.

[19] Subramanian, D., Subramaniam, S., Natarajan, K., & Thangavel, K. (2024). Flamingo Jelly Fish search optimization-based routing with deep-learning enabled energy prediction in WSN data communication. Network: Computation in Neural Systems, 35(1), 73-100.

[20] Sun, E., Cui, Y., Liu, P., & Yan, J. (2025). A decade of deep learning for remote sensing spatiotemporal fusion: Advances, challenges, and opportunities. arXiv preprint arXiv:2504.00901.