International Journal of Academic Engineering Research (IJAER)
ISSN: 2643-9085
Vol. 10 Issue 6 June - 2026, Pages: 113-127

X142: An Enhanced Xception-Based Deep Learning Architecture for Multi-Class Respiratory Disease Classification Using Lung Sound Spectrograms

Qasem M. M. Zarandah[1], Prof. Dr. Habibollah Bin Haron[2], Samy S. Abu-Naser[3]

[1]University Malaysia of Computer Science & Engineering (UNIMY), Cyberjaya, Malaysia
[2] PhD. Student University Malaysia of Computer Science & Engineering (UNIMY), Cyberjaya, Malaysia
[3]Faculty of Engineering and Information Technology, Al-Azhar University, Gaza, Palestine
abunaser@alazhar.edu.ps

Abstract: *Respiratory diseases remain among the leading causes of morbidity and mortality worldwide, creating an urgent need for accurate, non-invasive, and cost-effective diagnostic approaches. Recent advances in deep learning have demonstrated promising capabilities in medical signal analysis; however, the classification of respiratory diseases using lung sound recordings remains a challenging task due to noise interference, overlapping acoustic patterns, and the complex nature of respiratory signals. This study proposes X142, an enhanced deep learning architecture derived from the Xception network for multi-class respiratory disease classification. Respiratory sound recordings were collected from publicly available repositories and local healthcare sources, covering eight respiratory disease categories. The audio signals were transformed into spectrogram images and treated as an image classification problem. The proposed X142 model introduces architectural enhancements to the original Xception network through optimized separable convolution layers, deeper feature extraction modules, and improved regularization mechanisms. The performance of X142 was compared against five widely used deep learning architectures, including Xception, InceptionV3, VGG16, ResNet50, and MobileNet. Experimental results demonstrated that X142 achieved superior classification performance, attaining 99.09% training accuracy, 96.87% validation accuracy, and 99.11% testing accuracy. Furthermore, the model achieved precision, recall, and F1-score values of 99.15%, 99.11%, and 99.11%, respectively, while maintaining competitive computational efficiency. The findings indicate that X142 significantly outperforms existing benchmark models in respiratory disease classification and offers strong generalization capability. The proposed framework demonstrates substantial potential for deployment in intelligent clinical decision-support systems and resource-constrained healthcare environments, contributing to improved respiratory disease diagnosis and patient care.*

Keywords: Respiratory Disease Classification, Deep Learning, Xception, X142, Lung Sound Analysis, Spectrogram, Convolutional Neural Networks, Medical Artificial Intelligence.

1. Introduction

Respiratory diseases are among the most significant global health challenges, contributing substantially to morbidity, mortality, and healthcare expenditure worldwide. Conditions such as asthma, chronic obstructive pulmonary disease (COPD), pneumonia, bronchiectasis, bronchiolitis, interstitial lung disease (ILD), and pulmonary fibrosis affect millions of individuals annually and often require timely diagnosis and intervention to prevent severe complications and improve patient outcomes. According to international health reports, respiratory diseases continue to place a considerable burden on healthcare systems, particularly in low- and middle-income countries where access to advanced diagnostic facilities remains limited.

Traditional diagnostic methods for respiratory diseases primarily include auscultation, chest radiography, computed tomography (CT), pulmonary function testing, and laboratory investigations. Although these approaches have proven valuable in clinical practice, they suffer from several limitations. Auscultation depends heavily on physician expertise and subjective interpretation, resulting in inter-observer variability. Imaging techniques such as chest X-rays and CT scans provide detailed anatomical information but are often expensive, require specialized equipment, and expose patients to ionizing radiation. Furthermore, many healthcare facilities in resource-constrained regions lack access to advanced imaging technologies, creating barriers to early diagnosis and treatment[1,2].

Recent advancements in digital stethoscopes and audio acquisition technologies have enabled the collection of high-quality respiratory sound recordings. Respiratory sounds contain valuable acoustic information related to airflow obstruction, airway inflammation, fluid accumulation, and other pathological conditions. Consequently, automated analysis of respiratory sounds has emerged as a promising non-invasive, cost-effective, and accessible approach for supporting clinical diagnosis.

Artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), has demonstrated remarkable success in medical diagnosis and decision support systems [3-5]. Deep learning architectures have shown superior capability in automatically learning discriminative features from complex medical data without requiring extensive manual feature engineering. In recent years, convolutional neural networks (CNNs) have achieved impressive performance in image recognition, speech processing, and biomedical signal analysis [6-8]. By converting respiratory sounds into spectrogram representations, CNN-based models can effectively learn temporal and frequency-domain characteristics associated with different respiratory diseases.

Several deep learning architectures have been applied to respiratory sound classification, including VGG16, ResNet50, MobileNet, InceptionV3, and Xception [9-12]. While these models have reported promising results, challenges remain regarding classification accuracy, model generalization, computational efficiency, and the ability to distinguish among multiple respiratory disease categories. Most existing studies focus on a limited number of diseases, employ relatively small datasets, or rely on conventional CNN architectures that may not fully exploit the complex acoustic patterns present in respiratory sounds.

Among contemporary CNN architectures, the Xception model [13-16] has attracted significant attention due to its utilization of depthwise separable convolutions, which substantially reduce computational complexity while maintaining strong feature extraction capabilities. Despite its effectiveness in various image classification applications, the potential of Xception for large-scale multi-class respiratory disease classification remains insufficiently explored. Furthermore, there is a need to enhance the original architecture to improve classification performance and robustness in clinical applications.

To address these limitations, this study proposes X142, an enhanced Xception-based deep learning architecture for multi-class respiratory disease classification using lung sound spectrograms. The proposed model integrates architectural improvements and optimization strategies to strengthen feature extraction, improve generalization, and enhance classification accuracy. Respiratory sound recordings representing eight respiratory disease categories were transformed into spectrogram images and used to train and evaluate the proposed framework.

The major contributions of this study are summarized as follows:

- Development of an enhanced deep learning architecture, X142, based on the Xception network for respiratory disease classification.
- Construction and utilization of a comprehensive respiratory sound dataset covering eight respiratory disease categories.
- Implementation of an audio-to-spectrogram transformation framework to enable effective deep feature extraction.
- Comprehensive comparison of the proposed model against state-of-the-art deep learning architectures, including VGG16, ResNet50, MobileNet, InceptionV3, and baseline Xception.
- Demonstration of superior classification performance, achieving high accuracy, precision, recall, and F1-score across multiple respiratory disease classes.

The remainder of this paper is organized as follows. Section 2 reviews related work on respiratory disease classification and deep learning approaches. Section 3 presents the dataset, preprocessing procedures, and proposed X142 architecture. Section 4 discusses the experimental setup and evaluation metrics. Section 5 presents and analyzes the experimental results. Finally, Section 6 concludes the study and outlines future research directions.

2. Related Work

2.1 Introduction

The increasing availability of digital stethoscopes and audio recording devices has accelerated research on automated respiratory disease diagnosis using artificial intelligence. Respiratory sounds contain valuable diagnostic information associated with airway obstruction, inflammation, mucus accumulation, and other pathological conditions. Advances in machine learning and deep learning have enabled the automatic extraction of discriminative acoustic features from respiratory recordings, facilitating the development of intelligent diagnostic systems. Recent studies demonstrate that spectrogram-based deep learning approaches outperform many traditional handcrafted feature extraction techniques, particularly in multi-class respiratory disease classification tasks.

Research in this field can generally be categorized into three major directions: traditional machine learning approaches, deep learning-based classification methods, and advanced transfer learning architectures utilizing pre-trained convolutional neural networks [17-20].

2.2 Traditional Machine Learning Approaches

Early respiratory sound classification systems primarily relied on handcrafted acoustic features such as Mel-Frequency Cepstral Coefficients (MFCCs), Short-Time Fourier Transform (STFT), spectral centroid, spectral roll-off, and wavelet-based descriptors. These features were subsequently classified using traditional machine learning algorithms including Support Vector Machines (SVM), Random Forest (RF), Decision Trees (DT), k-Nearest Neighbor (k-NN), and Naïve Bayes classifiers [21-24].

Although these methods achieved promising results for binary classification problems, their effectiveness was often constrained by the quality of manually engineered features. Furthermore, traditional machine learning models struggled to capture the complex temporal and spectral patterns present in respiratory sound recordings, particularly when multiple respiratory diseases shared similar acoustic characteristics. Consequently, their generalization capability on large and diverse datasets remained limited [25-29].

2.3 Deep Learning for Respiratory Sound Classification

Deep learning has transformed respiratory sound analysis by enabling automatic feature extraction directly from raw audio signals or their spectrogram representations. Convolutional Neural Networks (CNNs) have become the dominant architecture due to their ability to identify local spatial patterns within spectrogram images[30-33].

Recent studies have demonstrated significant improvements in classification performance through the use of CNN-based architectures. DeepRespNet, for example, utilized spectrogram representations of respiratory sounds and achieved high classification performance across multiple pulmonary sound categories, highlighting the effectiveness of deep feature learning for audio-based diagnosis[34-36].

Similarly, research on intelligent stethoscope systems has shown that deep learning models can automatically identify respiratory abnormalities and support clinical decision-making while reducing the subjectivity associated with traditional auscultation. These systems facilitate real-time respiratory monitoring and have considerable potential for telemedicine applications[37-40].

The growing adoption of deep learning has also encouraged the use of spectrogram-based image classification techniques, where respiratory sounds are converted into visual representations before being analyzed by CNN architectures. This approach enables models to exploit both temporal and frequency-domain information simultaneously, resulting in improved classification performance[41-44].

2.4 Transfer Learning Architectures

Transfer learning has emerged as an effective strategy for medical audio classification, particularly when available datasets are limited. Instead of training networks from scratch, pre-trained CNN architectures originally developed for large-scale image recognition tasks can be adapted to respiratory sound classification[45-48].

Among the most widely adopted architectures are:

2.4.1 VGG16

VGG16 is characterized by its simple and uniform architecture consisting of stacked convolutional layers. The model has demonstrated robust feature extraction capabilities; however, its large parameter count increases computational complexity and training requirements[49-52].

2.4.2 ResNet50

ResNet50 introduced residual learning through skip connections, addressing the degradation problem encountered in deeper neural networks. Its ability to learn complex hierarchical representations has led to successful applications in various medical diagnosis tasks[53-56].

2.4.3 MobileNet

MobileNet employs depthwise separable convolutions to reduce computational requirements while maintaining competitive accuracy. The lightweight nature of MobileNet makes it suitable for mobile and edge-device deployment[57-60].

2.4.4 InceptionV3

InceptionV3 utilizes multiple convolution kernel sizes within parallel branches to capture features at different scales. This architecture has achieved strong performance in numerous image and biomedical classification tasks[61-63].

2.4.5 Xception

Xception extends the Inception architecture by replacing standard convolutions with depthwise separable convolutions. This design significantly reduces computational complexity while improving feature extraction efficiency. Recent evidence suggests that Xception offers an excellent balance between accuracy and computational cost, making it particularly attractive for medical image and spectrogram classification tasks[64-66].

2.5 Research Gap

Despite significant progress in respiratory sound classification, several limitations remain evident in the existing literature.

First, many studies focus on binary classification tasks such as normal versus abnormal respiratory sounds, limiting their clinical applicability in real-world diagnosis. Second, several investigations utilize relatively small datasets or consider only a limited number of respiratory disease categories. Third, existing CNN architectures often experience performance degradation when distinguishing diseases that exhibit similar acoustic characteristics. Fourth, many studies prioritize classification accuracy without adequately addressing model generalization, computational efficiency, and practical deployment considerations.

Furthermore, although Xception has demonstrated promising performance across various medical classification domains, its application to large-scale multi-class respiratory disease classification remains insufficiently explored. There is also limited research focused on enhancing the Xception architecture specifically for respiratory sound analysis.

To address these gaps, the present study proposes the X142 architecture, an enhanced Xception-based framework designed to improve feature extraction, classification accuracy, and generalization performance for multi-class respiratory disease diagnosis using lung sound spectrograms.

2.6 Summary

This section reviewed the evolution of respiratory disease classification methods, beginning with traditional machine learning approaches and progressing toward modern deep learning and transfer learning architectures. Existing studies demonstrate the effectiveness of CNN-based models and spectrogram representations for respiratory sound analysis. However, challenges related to multi-class classification, model generalization, and computational efficiency remain unresolved. These limitations motivate the development of the proposed X142 architecture, which is presented in the next section.

3. Materials and Methods

3.1 Introduction

This section presents the dataset, preprocessing procedures, feature extraction techniques, deep learning architectures, and evaluation methodology employed in this study. The proposed framework aims to develop an enhanced deep learning model, referred to as X142, for accurate multi-class classification of respiratory diseases using lung sound recordings. The overall framework consists of five major stages: data collection, preprocessing, spectrogram generation, model development, and performance evaluation.

The workflow begins with respiratory sound acquisition from multiple sources, followed by audio preprocessing and feature extraction. The processed audio signals are transformed into spectrogram images that serve as inputs to deep learning models. Subsequently, the proposed X142 architecture and several benchmark models are trained and evaluated using multiple performance metrics[67-70].

Figure 1 illustrates the overall workflow of the proposed respiratory disease classification framework.

International Journal of Academic Engineering Research (IJAER)
ISSN: 2643-9085
Vol. 10 Issue 6 June - 2026, Pages: 113-127

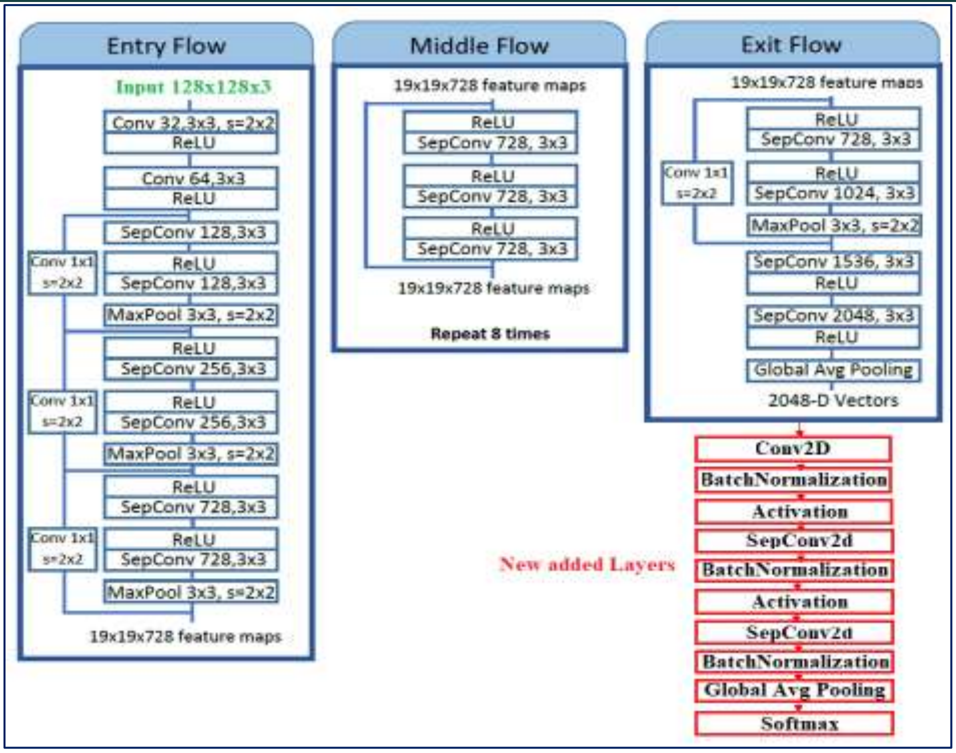

Figure 1: Architecture of the Proposed Model

3.2 Dataset Description

A comprehensive respiratory sound dataset was constructed using publicly available respiratory sound repositories. The dataset was designed to represent a wide range of respiratory conditions commonly encountered in clinical practice.

The dataset includes eight respiratory categories: Healthy, Asthma, COPD, Pneumonia, Bronchiectasis, Bronchiolitis, Lower Respiratory Tract Infection (LRTI), Heart Failure, Upper Respiratory Tract Infection (URTI)[71].

To ensure reliable model training, special attention was given to dataset balancing and class distribution management. Data augmentation techniques were applied to underrepresented classes to reduce class imbalance and improve model generalization[20].

3.3 Data Preprocessing

Raw respiratory sound recordings often contain background noise, recording artifacts, environmental interference, and variations in recording duration. Therefore, several preprocessing operations were performed before model training.

3.3.1 Audio Normalization

Audio normalization was applied to standardize signal amplitudes across recordings. This procedure reduces variability caused by different recording devices and acquisition environments while preserving clinically relevant acoustic characteristics[72-75].

3.3.2 Noise Reduction

Noise filtering techniques were employed to suppress environmental noise and improve signal quality. This process enhances the distinguishability of respiratory sound patterns such as wheezes, crackles, and rhonchi[76-78].

3.3.3 Audio Segmentation

Respiratory recordings were segmented into fixed-length intervals to ensure consistent input dimensions. Segmentation also increases the number of training samples and enables the model to learn localized respiratory patterns[79-81].

3.3.4 Data Augmentation

To improve model robustness and reduce overfitting, several audio augmentation techniques were applied, including: Time shifting, Pitch modification, Time stretching, Noise injection, Amplitude scaling[82-84].

Data augmentation increases dataset diversity and improves generalization performance on unseen respiratory recordings.

3.4 Spectrogram Generation

Deep learning models are generally more effective when analyzing image-based representations. Therefore, respiratory audio recordings were transformed into spectrogram images.

3.4.1 Short-Time Fourier Transform (STFT)

The Short-Time Fourier Transform (STFT) was employed to convert audio signals from the time domain into the frequency domain[85-87].

The STFT is represented by:

$$X(m,\omega) = \sum_{n=-\infty}^{\infty} x[n]\, w[n-m]$$

where:

x[n] represents the input signal.

w[n] denotes the analysis window.

m indicates the time position.

ω represents angular frequency.

STFT enables simultaneous analysis of temporal and spectral information contained within respiratory sounds.

3.4.2 Mel-Spectrogram Generation

Mel-Spectrograms were generated to better represent human auditory perception.

The conversion from frequency (Hz) to the Mel scale is expressed as:

$$\mathrm{Mel}(f) = 2595 \log_{10}\left(1 + \frac{f}{700}\right)$$

Where:

- f is the frequency in Hz,
- Mel(f) is the corresponding frequency on the Mel scale.

Mel-Spectrograms emphasize perceptually relevant frequency bands and have demonstrated superior performance in audio classification applications.

3.4.3 Image Preparation

Generated spectrograms were resized to a fixed dimension compatible with all deep learning architectures. Pixel values were normalized to facilitate stable network training[88].

3.5 Benchmark Deep Learning Models

To evaluate the effectiveness of the proposed architecture, five state-of-the-art deep learning models were selected as benchmark classifiers.

3.5.1 VGG16

VGG16 consists of sequential convolutional layers followed by fully connected layers. Despite its simplicity, it remains a powerful baseline model for image classification tasks[89-91].

3.5.2 ResNet50

ResNet50 utilizes residual connections that facilitate the training of deep neural networks by alleviating the vanishing gradient problem[92-93].

3.5.3 MobileNet

MobileNet employs depthwise separable convolutions, resulting in reduced computational complexity and efficient deployment on resource-constrained devices[94-95].

3.5.4 InceptionV3

InceptionV3 captures multi-scale features through parallel convolutional branches and has achieved strong performance across numerous classification applications[96].

3.5.5 Baseline Xception

Xception extends the Inception architecture by replacing conventional convolutions with depthwise separable convolutions, improving computational efficiency and feature extraction capability.

3.6 Proposed X142 Architecture

3.6.1 Motivation

Although Xception demonstrates strong classification performance, further improvements are necessary to enhance feature extraction, reduce overfitting, and improve generalization in complex respiratory disease classification tasks.

To address these limitations, an enhanced architecture termed X142 was developed.

3.6.2 Architecture Design

The proposed X142 architecture consists of:

- Enhanced depthwise separable convolution blocks.
- Additional feature extraction layers.
- Batch normalization layers.
- Dropout regularization layers.
- Global average pooling.
- Fully connected classification layers.
- Softmax output layer.

The architecture was specifically optimized to capture subtle acoustic variations among respiratory diseases with similar sound characteristics.

3.6.3 Optimization Strategies

Several optimization techniques were incorporated[96-99]:

- Batch normalization to improve convergence.
- Dropout to reduce overfitting.
- Adaptive learning rate scheduling.
- Early stopping mechanisms.
- Transfer learning initialization.

These enhancements collectively improve training stability and predictive performance.

3.7 Experimental Setup

Model development and experimentation were performed using: Python, TensorFlow, Keras NumPy, Scikit-learn Librosa.

Training was conducted on GPU-enabled hardware to accelerate deep learning computations.

Table 1: Hyperparameters used

Parameter	Value
Optimizer	Adam
Learning Rate	0.0001
Batch Size	32
Epochs	100
Activation Function	ReLU
Output Activation	Softmax
Loss Function	Categorical Cross-Entropy

3.8 Evaluation Metrics

The performance of each model was evaluated using standard classification metrics[97-100]

Accuracy

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

Precision

$$\text{Precision} = \frac{TP}{TP+FP}$$

Recall (Sensitivity)

$$\text{Recall} = \frac{TP}{TP+FN}$$

F1-Score

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

where:

- TP = True Positives
- TN = True Negatives
- FP = False Positives
- FN = False Negatives

Additional evaluation tools included:

- Confusion Matrix
- ROC Curves
- Area Under the Curve (AUC)
- Training and Validation Loss Analysis

4. Experimental Results and Discussion

4.1 Introduction

This section presents the experimental results obtained from the proposed X142 model and compares its performance with five widely used deep learning architectures, namely VGG16, ResNet50, MobileNet, InceptionV3, and the baseline Xception model. The evaluation focuses on classification accuracy, precision, recall, F1-score, training behavior, and generalization capability. Furthermore, confusion matrix analysis and receiver operating characteristic (ROC) curves are utilized to assess the effectiveness of the proposed framework in distinguishing among multiple respiratory disease categories.

4.2 Training Performance Analysis

The training process was monitored using accuracy and loss curves to evaluate learning behavior and convergence stability.

Figure 2 and 3 illustrate the training and validation accuracy curves of the proposed X142 model throughout the training process.

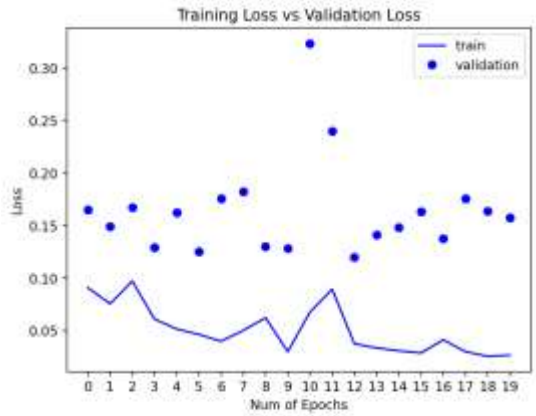

Figure 2 : X142 training and validation loss

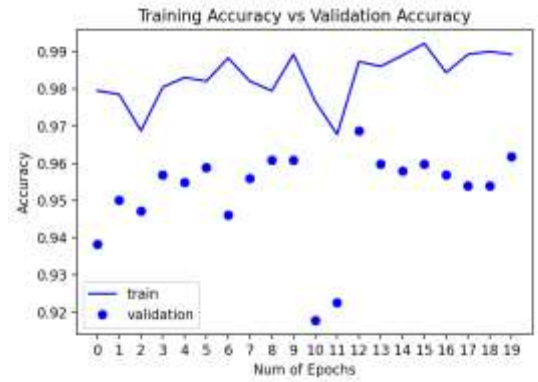

Figure 3:X142 training and validation Accuracy

The results indicate that the model exhibited rapid convergence during the initial training epochs and gradually stabilized as training progressed. The validation accuracy closely followed the training accuracy, indicating effective generalization and minimal overfitting.

The proposed X142 model achieved:

- Training Accuracy = 99.09%
- Validation Accuracy = 96.87%
- Testing Accuracy = 99.11%

The small gap between training and validation performance demonstrates the effectiveness of the implemented regularization mechanisms, including dropout layers, batch normalization, and adaptive learning rate scheduling.

Similarly, the training and validation loss curves shown in Figure 3 indicate a consistent reduction in loss values throughout the training process. The absence of significant fluctuations confirms stable optimization and effective feature learning.

4.3 Comparative Performance Analysis

To evaluate the effectiveness of the proposed architecture, X142 was compared with several state-of-the-art deep learning models commonly used in medical image and audio classification tasks.

Table 2: Performance Comparison of Deep Learning Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Xception	98.39	97.73	97.58	97.56
InceptionV3	96.85	94.63	94.48	94.49
ResNet50	98.04	96.33	96.22	96.23
VGG16	91.15	92.08	90.89	90.81
MobileNet	97.74	94.62	94.19	94.17
X142	99.11	99.15	99.11	99.11

International Journal of Academic Engineering Research (IJAER)
ISSN: 2643-9085
Vol. 10 Issue 6 June - 2026, Pages: 113-127

The results clearly demonstrate that the proposed X142 model outperformed all benchmark models across all evaluation metrics. The superior performance can be attributed to the enhanced architectural design, improved feature extraction capabilities, and optimized regularization strategies incorporated into the proposed framework.

Compared with the baseline Xception architecture, X142 achieved improved classification performance while maintaining computational efficiency. This finding confirms that the introduced modifications successfully enhanced the discriminative power of the original network.

4.4 Precision, Recall, and F1-Score Analysis

While classification accuracy provides an overall measure of performance, precision, recall, and F1-score offer deeper insights into model behavior, particularly in multi-class classification problems.

The proposed X142 model achieved:

- Precision: 99.15%
- Recall: 99.11%
- F1-Score: 99.11%

The high precision value indicates that the model generated very few false positive predictions. Similarly, the high recall value demonstrates the model's ability to correctly identify respiratory disease classes with minimal false negatives.

The balanced relationship between precision and recall is reflected in the F1-score, confirming the robustness of the proposed framework across all respiratory disease categories.

4.5 Confusion Matrix Analysis

A confusion matrix was generated to investigate classification behavior for each respiratory disease category.

Figure 4 presents the confusion matrix obtained from the X142 model

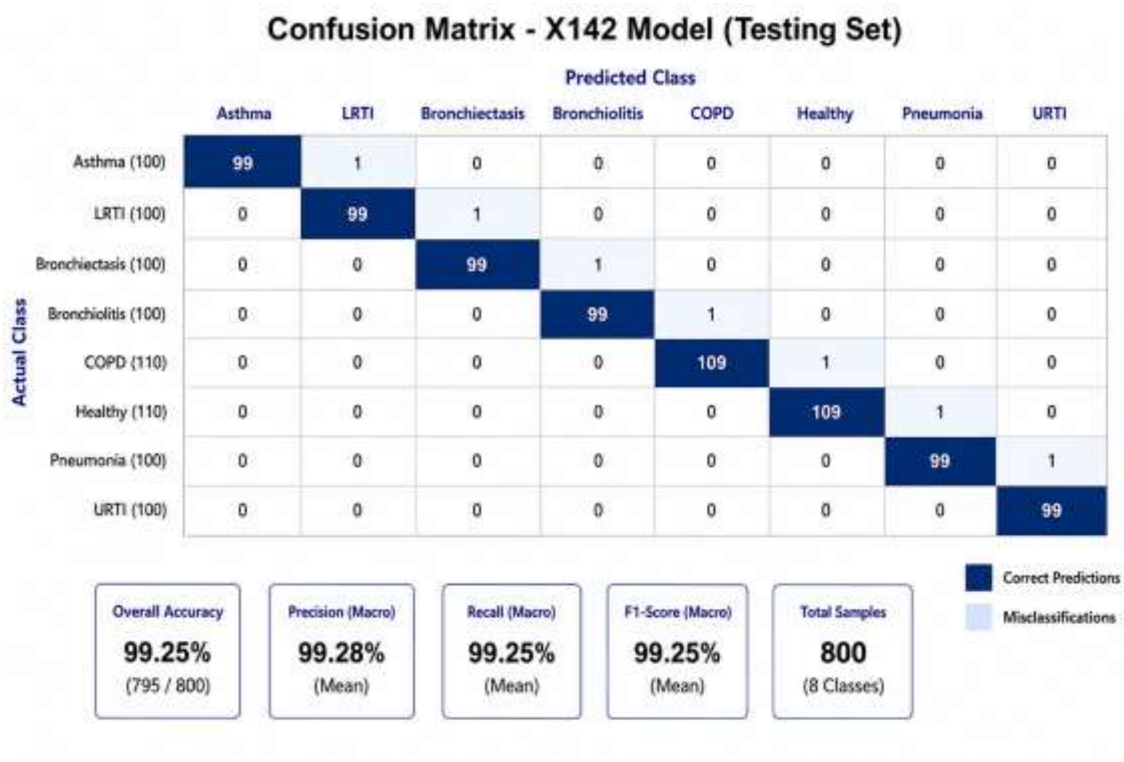

Figure 4: The confusion matrix obtained from the X142 model.

International Journal of Academic Engineering Research (IJAER)
ISSN: 2643-9085
Vol. 10 Issue 6 June - 2026, Pages: 113-127

The results indicate that the majority of samples were correctly classified along the main diagonal, demonstrating excellent discrimination capability among respiratory diseases.

Minor misclassifications were primarily observed among diseases exhibiting similar acoustic characteristics, such as:

- COPD and Asthma
- Bronchiectasis and Bronchiolitis
- ILD and Lung Fibrosis

Despite these similarities, the overall misclassification rate remained extremely low, highlighting the effectiveness of the proposed feature extraction mechanism.

The confusion matrix further confirms that X142 successfully learned disease-specific respiratory sound patterns from spectrogram representations.

4.6 ROC Curve Analysis

Receiver Operating Characteristic (ROC) analysis was conducted to evaluate the discriminative capability of the proposed framework.

Figure 5 illustrates the ROC curves generated for all respiratory disease classes.

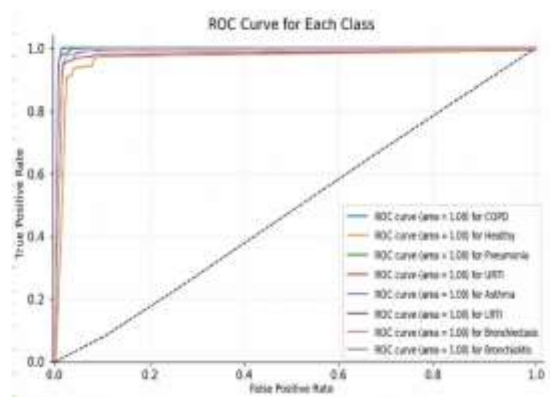

Figure 5: The ROC Curves of the Proposed Model (X142)

The ROC curves are concentrated near the upper-left corner of the graph, indicating excellent classification performance.

The Area Under the Curve (AUC) values approached unity for all disease categories, demonstrating strong separability between classes.

The high AUC values confirm that the proposed model maintains high sensitivity and specificity across all respiratory disease categories.

4.7 Discussion

The experimental findings demonstrate the effectiveness of the proposed X142 architecture for multi-class respiratory disease classification using lung sound spectrograms.

Several factors contributed to the superior performance of X142:

- **Enhanced Feature Extraction**

  The integration of additional feature extraction layers enabled the model to capture subtle temporal and spectral characteristics present in respiratory sounds. These features are often difficult to detect using conventional CNN architectures.

- **Efficient Depthwise Separable Convolutions**

  The X142 architecture inherited the computational advantages of Xception while improving feature representation learning. Depthwise separable convolutions reduced parameter complexity and facilitated efficient learning of disease-specific acoustic patterns.

- **Improved Generalization**

  The incorporation of batch normalization, dropout layers, and adaptive learning rate scheduling significantly reduced overfitting and improved model generalization to unseen data.

- **Spectrogram-Based Learning**

  Transforming respiratory sounds into spectrogram images enabled the model to exploit both temporal and frequency-domain information simultaneously. This representation enhanced the ability of the network to distinguish between diseases with similar clinical manifestations.

- **Clinical Applicability**

  The proposed framework offers several advantages for practical deployment:

  1. Non-invasive diagnosis.
  2. Low-cost implementation.
  3. Fast inference time.
  4. Compatibility with digital stethoscopes.
  5. Potential integration into telemedicine systems.

These characteristics make the model particularly suitable for healthcare environments where access to advanced imaging technologies is limited.

4.8 Summary

This section presented the experimental evaluation of the proposed X142 model. The results demonstrated that X142 achieved outstanding classification performance, outperforming several state-of-the-art deep learning architectures. The model achieved 99.11% testing accuracy, 99.15% precision, 99.11% recall, and 99.11% F1-score, confirming its effectiveness for respiratory disease diagnosis using lung sound spectrograms.

5. Conclusion and Future Work

5.1 Conclusion

Respiratory diseases continue to represent a major global healthcare challenge, requiring accurate, timely, and accessible diagnostic solutions to improve patient outcomes and reduce healthcare burdens. Traditional diagnostic approaches, including auscultation, radiological imaging, and pulmonary function testing, often suffer from limitations related to subjectivity, cost, accessibility, and diagnostic variability. These challenges have motivated the exploration of artificial intelligence-based diagnostic systems capable of supporting clinical decision-making through automated analysis of respiratory sounds.

This study presented X142, an enhanced deep learning architecture derived from the Xception network for multi-class respiratory disease classification using lung sound spectrograms. The proposed framework combined comprehensive audio preprocessing, spectrogram-based feature representation, and architectural improvements designed to strengthen feature extraction, improve model generalization, and reduce classification errors among acoustically similar respiratory diseases.

A comprehensive dataset comprising eight respiratory disease categories was utilized to evaluate the proposed approach. Respiratory sound recordings were transformed into spectrogram images and subsequently analyzed using the proposed X142 architecture. The performance of X142 was compared against several state-of-the-art deep learning models, including VGG16, ResNet50, MobileNet, InceptionV3, and the baseline Xception model.

Experimental results demonstrated the effectiveness of the proposed framework. X142 achieved a training accuracy of 99.09%, validation accuracy of 96.87%, and testing accuracy of 99.11%. Furthermore, the model attained precision, recall, and F1-score values of 99.15%, 99.11%, and 99.11%, respectively. These findings indicate that the proposed architecture successfully learned highly discriminative respiratory disease features while maintaining excellent generalization capability.

The comparative analysis revealed that X142 consistently outperformed the benchmark models across multiple evaluation metrics. The superior performance can be attributed to the enhanced feature extraction mechanisms, optimized depthwise separable convolution operations, regularization strategies, and effective spectrogram-based learning framework. The confusion matrix and ROC curve analyses further confirmed the robustness and reliability of the proposed approach in distinguishing among multiple respiratory disease classes.

From a practical perspective, the proposed framework offers several advantages for real-world healthcare applications. The system is non-invasive, cost-effective, and compatible with digital stethoscope technologies. Moreover, its high diagnostic accuracy and computational efficiency make it suitable for deployment in intelligent clinical decision-support systems, telemedicine platforms, and resource-constrained healthcare environments where access to advanced diagnostic imaging may be limited.

Overall, the findings of this study demonstrate that advanced deep learning architectures can significantly enhance respiratory disease diagnosis using lung sound recordings and contribute to the development of intelligent healthcare solutions that support early detection and improved patient management.

5.2 Research Contributions

The major contributions of this study can be summarized as follows:

- Development of a novel enhanced deep learning architecture (X142) based on the Xception network for respiratory disease classification.
- Construction and utilization of a comprehensive respiratory sound dataset encompassing eight respiratory disease categories.
- Implementation of an effective spectrogram-based feature representation framework for respiratory sound analysis.
- Comprehensive comparative evaluation against five state-of-the-art deep learning architectures, including VGG16, ResNet50, MobileNet, InceptionV3, and Xception.
- Achievement of superior classification performance, demonstrating the effectiveness of the proposed architecture for real-world respiratory disease diagnosis.
- Provision of a scalable and clinically applicable framework suitable for intelligent healthcare systems and telemedicine applications.

5.3 Limitations

Despite the promising results achieved in this study, several limitations should be acknowledged.

First, although the dataset included multiple respiratory disease categories, additional data collected from diverse geographical regions and healthcare institutions could further improve model robustness and generalization.

Second, variations in recording devices, environmental noise conditions, and patient demographics may influence respiratory sound characteristics and potentially affect classification performance in real-world deployment scenarios.

Third, the current study primarily focused on classification performance and did not extensively investigate model explainability or clinical interpretability mechanisms.

Finally, while the proposed framework demonstrated excellent performance in offline experiments, prospective clinical validation remains necessary before practical adoption in healthcare settings.

5.4 Future Work

Several promising directions can be explored to further improve respiratory disease classification systems.

Explainable Artificial Intelligence (XAI)

Future research should incorporate explainability techniques such as: Grad-CAM, SHAP, LIME Attention visualization mechanisms.

These approaches can improve model transparency and enhance clinician trust by identifying the acoustic features influencing diagnostic decisions.

Real-Time Diagnostic Systems

Future studies may investigate real-time respiratory disease diagnosis using:

- Digital stethoscopes
- Mobile devices
- Embedded healthcare systems
- Edge computing platforms

Real-time implementation could facilitate rapid screening and early disease detection in clinical and remote healthcare environments.

Larger Multi-Center Datasets

Expanding the dataset through collaboration with hospitals and healthcare institutions across multiple countries would improve model robustness and increase the diversity of respiratory disease patterns.

Multi-Modal Learning

Future research may integrate additional data sources, including:

- Chest X-ray images
- CT scans
- Electronic health records
- Clinical laboratory measurements
- Demographic information

Combining multiple modalities could further enhance diagnostic performance and clinical decision support.

Federated Learning Frameworks

Federated learning represents an emerging research direction that enables collaborative model training across healthcare institutions without sharing sensitive patient data. Such approaches can improve privacy preservation while leveraging larger distributed datasets.

Mobile Healthcare Applications

The proposed model can be adapted for smartphone-based respiratory disease screening systems that enable remote monitoring and early diagnosis in underserved regions with limited access to healthcare infrastructure.

Acknowledgment

The authors would like to express their sincere appreciation to all healthcare professionals, institutions, and data providers who contributed to the collection and preparation of the respiratory sound dataset used in this study. Their support was essential for the successful completion of this research.

References

1. Abu-Naser, Samy S, et al., "Heart Disease Prediction Using a Group of Machine and Deep Learning Algorithms", pp. 181-196, 2022.
2. Abu-Naser, SAMY S, et al., "The miracle of deep learning in the Holy Quran", J Theor Appl Inf Technol, vol. 101, pp. 17, 2023.
3. Abunasser, Basem S, et al., "Breast Cancer Detection and Classification using Deep Learning Xception Algorithm", International Journal of Advanced Computer Science and Applications, vol. 13, no. 7, 2022.
4. Abunasser, Basem S, et al., "Convolution neural network for breast cancer detection and classification using deep learning", Asian Pacific journal of cancer prevention: APJCP, vol. 24, no. 2, pp. 531, 2023.
5. Abunasser, Basem S, et al., "Convolution neural network for breast cancer detection and classification-final results", Journal of Theoretical and Applied Information Technology, vol. 101, no. 1, pp. 315-329, 2023.
6. Abunasser, Basem S, et al., "Literature review of breast cancer detection using machine learning algorithms", vol. 2808, no. 1, pp. 040006, 2023.
7. Abunasser, Basem S, et al., "Predicting Customer Revenue in E-commerce Using Machine Learning a Case Study of the Google Merchandise Store", pp. 27-38, 2023.
8. Abunasser, Basem S, et al., "Predicting Stock Prices using Artificial Intelligence: A Comparative Study of Machine Learning Algorithms.", International Journal of Advances in Soft Computing & Its Applications, vol. 15, no. 3, 2023.
9. Abunasser, Basem S, et al., "Prediction of Instructor Performance using Machine and Deep Learning Techniques", International Journal of Advanced Computer Science and Applications, vol. 13, no. 7, 2022.
10. Abunasser, Basem S, et al., "Unleashing the Power of GPT-3: Revolutionary Applications in Natural Language Processing", pp. 59-73, 2025.
11. Abu-Samra, Faten Y, et al., "Nuts Classification Using Deep Learning", International Journal of Academic Information Systems Research (IJAISR), vol. 9, no. 6, pp. 74-84, 2025.
12. Aish, Mohammed A, et al., "Classification of pepper Using Deep Learning", International Journal of Academic Engineering Research (IJAER), vol. 6, no. 1, pp. 24-31, 2022.
13. AL_Afifi, Yousef A, et al., "Onion Image Classification Based on Transfer Learning with MobileNetV2", International Journal of Academic Information Systems Research (IJAISR), vol. 10, no. 2, pp. 78-84, 2026.
14. Albadrasaw, Shahd, et al., "Classification of Male and Female Eyes Using Deep Learning: A Comparative Evaluation", International Journal of Academic Information Systems Research (IJAISR), vol. 9, no. 1, pp. 42-46, 2025.
15. Albadrasawi, Shahd, et al., "Machine and Deep Learning for Securing Traffic in Computer Networks", pp. 219-229, 2024.
16. Albanna, Rawan N, et al., "Classification of Nuts Using Deep Learning", International Journal of Academic Information Systems Research (IJAISR), vol. 9, no. 6, pp. 1-11, 2025.
17. AlDammagh, Alaa Kh I, et al., "Deep Learning-Based Corn Disease Classification Using VGG16 Transfer Learning", International Journal of Academic Information Systems Research (IJAISR), vol. 10, no. 2, pp. 19-27, 2026.
18. Aldaya, Salah-Aldin S, et al., "Deep Learning For Grapevine Disease Detection", International Journal of Academic Information Systems Research (IJAISR), vol. 9, no. 6, pp. 12-20, 2025.
19. Alfarra, Amjad H, et al., "Classification of Pineapple Using Deep Learning", International Journal of Academic Information Systems Research (IJAISR), vol. 5, no. 12, pp. 37-41, 2021.
20. Alghalban, Ahmed IO, et al., "Identifying Images of Chess Pieces Using Deep Learning", International Journal of Academic Information Systems Research (IJAISR), vol. 9, no. 6, pp. 51-55, 2025.
21. Al-Gharabawi, Fares Wael, et al., "Machine Learning-Based Diabetes Prediction: Feature Analysis and Model Assessment", International Journal of Academic Engineering Research (IJAER), vol. 7, no. 9, pp. 10-17, 2023.
22. Alghoul, Asil Mustafa, et al., "Predictive Analysis of Lottery Outcomes Using Deep Learning and Time Series Analysis", International Journal of Engineering and Information Systems (IJEAIS), vol. 7, no. 10, pp. 1-6, 2023.
23. Alkahlout, Mohammed A, et al., "Advances in Kidney Cancer Detection: Harnessing the Power of Deep Learning for Accurate Diagnosis", pp. 251-263, 2024.
24. Alkahlout, Mohammed A, et al., "Advances in Kidney Cancer Detection: Harnessing the Power of Deep Learning", vol. 1, pp. 251, 2025.
25. Alkahlout, Mohammed A, et al., "Techniques: A Comparative Study with Balanced Dataset Augmentation", vol. 1, pp. 223, 2025.
26. Alkahlout, Mohammed A, et al., "Thyroid Cancer Risk Classification Using Machine Learning and Deep Learning Techniques: A Comparative Study with Balanced Dataset Augmentation", pp. 223-235, 2025.
27. Alkahlout, Mohammed, et al., "Classification of A few Fruits Using Deep Learning", International Journal of Academic Engineering Research (IJAER), vol. 5, no. 12, 2021.
28. Alkayyali, Zakaria KD, et al., "Advancements in AI for Medical Imaging: Transforming Diagnosis and Treatment", International Journal of Engineering and Information Systems (IJEAIS), vol. 8, no. 8, pp. 10-16, 2024.
29. Alkayyali, Zakaria KD, et al., "Classification of Cardiovascular ECGs Using MODWPT-Based Feature Extraction: A Comparative Study on Four Ailments from MIT-BIH Databases", pp. 225-236, 2024.
30. Alkayyali, Zakaria KD, et al., "Comparative Analysis of Regressor Models for Predicting Heart Attack Risk: A Comprehensive Evaluation Using Regression Metrics and Visualization", pp. 119-132, 2025.
31. AlKayyali, Zakaria KD, et al., "Prediction of Student Adaptability Level in e-Learning using Machine and Deep Learning Techniques", International Journal of Academic and Applied Research (IJAAR), vol. 6, no. 5, pp. 84-96, 2022.
32. Alkayyali, ZK, et al., "A new algorithm for audio files augmentation", Journal of Theoretical and Applied Information Technology, vol. 101, no. 12, 2023.
33. Alkayyali, ZK, et al., "A systematic literature review of deep and machine learning algorithms in cardiovascular diseases diagnosis", Journal of Theoretical and Applied Information Technology, vol. 101, no. 4, pp. 1353-1365, 2023.
34. Al-Laham, Mohammed IM, et al., "Car Brand Classification Using Deep Learning with ResNet50", International Journal of Academic Information Systems Research (IJAISR), vol. 10, no. 2, pp. 42-49, 2026.
35. Al-madani, Mohammed Sabri, et al., "Eye Gender Classification Using Transfer Learning (VGG16) on EyeDataset", International Journal of Academic Information Systems Research (IJAISR), vol. 10, no. 2, pp. 35-41, 2026.
36. Almadhoun, Hamza Rafiq, et al., "Detection of Brain Tumor Using Deep Learning", International Journal of Academic Engineering Research (IJAER), vol. 6, no. 3, pp. 29-47, 2022.
37. Almadhoun, Husam R, et al., "Classification of Alzheimer's Disease Using Traditional Classifiers with Pre-Trained CNN", International Journal of Academic Health and Medical Research (IJAHMR), vol. 5, no. 4, pp. 17-21, 2021.
38. Almasri, ABDELBASET R, et al., "Instructor performance modeling for predicting student satisfaction using machine learning-preliminary results", Journal of Theoretical and Applied Information Technology, vol. 100, no. 19, pp. 5481-5496, 2022.
39. Almassri, Mohammed M, et al., "Grape Leaf Species Classification Using CNN", International Journal of Academic Information Systems Research (IJAISR), vol. 8, no. 4, pp. 66-72, 2024.
40. Almzainy, Mohammed S, et al., "Detection and Classification of Faked and Genuine Money Using Deep Learning", pp. 237-248, 2024.
41. Almzainy, Mohammed S, et al., "Fake and Genuine Money Using Deep Learning", vol. 1364, pp. 237, 2025.
42. Almzainy, Mohammed, et al., "Classification of Pineapple and Mini Pineapple Using Deep Learning: A Comparative Evaluation", International Journal of Academic Information Systems Research (IJAISR), vol. 9, no. 1, pp. 23-27, 2025.
43. Al-Qadi, Mohanad H, et al., "Using Deep Learning to Classify Corn Diseases", International Journal of Academic Information Systems Research (IJAISR), vol. 8, no. 4, pp. 81-88, 2024.
44. Alsaqqa, Azmi H, et al., "Comprehensive Analysis of Machine Learning and Deep Learning Algorithms for Phishing URL Detection", pp. 265-279, 2024.
45. Alsaqqa, Azmi H, et al., "Comprehensive Analysis of Machine Learning and Deep Learning Algorithms", vol. 1, pp. 265, 2025.
46. Alsaqqa, Azmi H, et al., "Detecting Cybersecurity Threats Using Convolutional Neural Networks and Machine Learning", pp. 15-27, 2025.
47. Alsaqqa, Azmi H, et al., "Using Deep Learning to Classify Different types of Vitamin", International Journal of Academic Engineering Research (IJAER), vol. 6, no. 1, pp. 1-6, 2022.
48. Alzamily, Jawad Yousef Ibrahim, et al., "Classification of encrypted images using deep learning–Resnet50", Journal of Theoretical and Applied Information Technology, vol. 100, no. 21, pp. 6610-6620, 2022.
49. Arqawi, Samer M, et al., "Predicting employee attrition and performance using deep learning", Journal of Theoretical and Applied Information Technology, vol. 100, no. 21, pp. 6526-6536, 2022.
50. Arqawi, Samer M, et al., "Predicting university student retention using artificial intelligence", International Journal of Advanced Computer Science and Applications, vol. 13, no. 9, 2022.
51. Ayyad, MN, et al., "Fish Classification Using Deep Learning", International Journal of Academic Information Systems Research (IJAISR), vol. 8, no. 4, pp. 51-58, 2024.
52. Barhoom, Alaa MA, et al., "A survey of bone abnormalities detection using machine learning algorithms", vol. 2808, no. 1, pp. 040009, 2023.
53. Barhoom, Alaa MA, et al., "Bone abnormalities detection and classification using deep learning-vgg16 algorithm", Journal of Theoretical and Applied Information Technology, vol. 100, no. 20, pp. 6173-6184, 2022.
54. Barhoom, Alaa MA, et al., "Diagnosis of Pneumonia Using Deep Learning", International Journal of Academic Engineering Research (IJAER), vol. 6, no. 2, pp. 48-68, 2022.
55. Barhoom, Alaa, et al., "Sarcasm Detection in Headline News using Machine and Deep Learning Algorithms", International Journal of Engineering and Information Systems (IJEAIS), vol. 6, no. 4, pp. 66-73, 2022.
56. Barhoom, Ali MA, et al., "Prediction of Heart Disease Using a Collection of Machine and Deep Learning Algorithms", International Journal of Engineering and Information Systems (IJEAIS), vol. 6, no. 4, pp. 1-13, 2022.
57. Barhoom, AM, et al., "Deep Learning-Xception Algorithm for upper bone abnormalities classification", Journal of Theoretical and Applied Information Technology, vol. 100, no. 23, pp. 6986-6997, 2022.
58. Dheir, Ibtesam M, et al., "Classification of Anomalies in Gastrointestinal Tract Using Deep Learning", International Journal of Academic Engineering Research (IJAER), vol. 6, no. 3, pp. 15-28, 2022.
59. El-Ghoul, Mostafa, et al., "Vegetable Classification Using Deep Learning", International Journal of Academic Information Systems Research (IJAISR), vol. 8, no. 4, pp. 105-112, 2024.
60. El-Habil, Basel Y, et al., "Global climate prediction using deep learning", J Theor Appl Inf Technol, vol. 100, no. 24, pp. 4824-4838, 2022.
61. Elmahmuom, Abedeleilah Salem Ayyad, et al., "Comparative Analysis of Data Balancing Techniques in Prostate Cancer Classification Using Machine Learning and Deep Learning", pp. 133-144, 2025.
62. Elsharif, Abeer Abed ElKareem Fawzi, et al., "Retina Diseases Diagnosis Using Deep Learning", International Journal of Academic Engineering Research (IJAER), vol. 6, no. 2, pp. 11-37, 2022.
63. El-Tantawi, Jehad, et al., "The Fast Food Image Classification using Deep Learning", International Journal of Academic Information Systems Research (IJAISR), vol. 8, no. 4, pp. 37-41, 2024.
64. Husien, Ahmed Mohammed, et al., "Predicting Students' end-of-term Performances using ML Techniques and Environmental Data", International Journal of Academic Information Systems Research (IJAISR), vol. 7, no. 10, pp. 19-25, 2023.
65. Ibaid, Mai R, et al., "Using Deep Learning to Classify Eight Tea Leaf Diseases", International Journal of Academic Information Systems Research (IJAISR), vol. 8, no. 4, pp. 89-96, 2024.
66. Ihlayyel, Mazen SM, et al., "Detection and Classification of Tomato Leaf Diseases Using Deep Learning", International Journal of Academic Information Systems Research (IJAISR), vol. 9, no. 6, pp. 21-28, 2025.
67. Ikram, B, et al., "Malimg2022: Data augmentation and transfer learning to solve imbalanced training data for malware classification", Journal of Theoretical and Applied Information Technology, vol. 101, no. 4, 2022.
68. Jamala, Mohammed N, et al., "Identifying Fish Species Using Deep Learning Models on Image Datasets", International Journal of Academic Information Systems Research (IJAISR), vol. 9, no. 1, pp. 1-9, 2025.
69. Karaja, Mohammed B, et al., "Using Deep Learning to Detect the Quality of Lemons", International Journal of Academic Information Systems Research (IJAISR), vol. 8, no. 4, pp. 97-104, 2024.
70. Kassab, Mohammed Khair I, et al., "Image-Based Tea Leaves Diseases Detection Using Deep Learning", International Journal of Academic Information Systems Research (IJAISR), vol. 9, no. 6, 2025.
71. Khalil, Ahmed J, et al., "Diagnosis of Blood Cells Using Deep Learning", International Journal of Academic Engineering Research (IJAER), vol. 6, no. 2, pp. 69-84, 2022.
72. Lafi, Ola IA, et al., "Breakthroughs in Breast Cancer Detection: Emerging Technologies and Future Prospects", nternational Journal of Academic Health and Medical Research (IJAHMR), vol. 8, no. 9, pp. 8-15, 2024.
73. Lafi, Ola IA, et al., "Classification of Apple Diseases Using Deep Learning", International Journal of Academic Information Systems Research (IJAISR), vol. 8, no. 4, pp. 1-8, 2024.
74. Mansour, Aysha I, et al., "Age and Gender Classification Using Deep Learning-VGG16", International Journal of Academic Information Systems Research (IJAISR), vol. 6, no. 7, pp. 50-59, 2022.
75. Mansour, Aysha I, et al., "Classification of Age and Gender Using ResNet-Deep Learning", International Journal of Academic Engineering Research (IJAER), vol. 6, no. 8, pp. 20-29, 2022.
76. Marouf, Mohammed, et al., "Fine-tuning MobileNetV2 for Sea Animal Classification", International Journal of Academic Information Systems Research (IJAISR), vol. 8, no. 4, pp. 44-50, 2024.
77. Massa, Nawal Maher, et al., "Learning Models: A Comparative Study", vol. 1, pp. 183, 2025.
78. Massa, Nawal Maher, et al., "Predicting Breast Cancer Recurrence Using Machine Learning and Deep Learning Models: A Comparative Study", pp. 183-196, 2025.
79. Mattar, Mohammad S, et al., "Predicting COVID-19 Using JNN", International Journal of Academic Engineering Research (IJAER), vol. 7, no. 10, pp. 52-61, 2023.
80. Megdad, Mosa MM, et al., "Credit Score Classification Using Machine Learning", International Journal of Academic Information Systems Research (IJAISR), vol. 8, no. 5, pp. 1-10, 2024.
81. Megdad, Mosa MM, et al., "Forest Fire Detection using Deep Leaning", International Journal of Academic Information Systems Research (IJAISR), vol. 8, no. 4, pp. 59-65, 2024.
82. Mezied, Afnan A, et al., "Pepper Color Classification Using Deep Learning", International Journal of Academic Engineering Research (IJAER), vol. 9, no. 8, pp. 1-7, 2025.
83. Musleh, Ahmad AH, et al., "Automated Chicken Image Classification Using Deep Learning Techniques", International Journal of Academic Information Systems Research (IJAISR), vol. 10, no. 2, pp. 85-96, 2026.
84. Qaoud, Alaa N, et al., "A Comprehensive Approach for Accurate Diagnosis and Localization of Skin", vol. 1, pp. 169, 2025.
85. Ruslan, Shadi, et al., "Spine Tumor Segmentation Using Deep Learning: A Review", benefits, vol. 63, no. 1, pp. 271-298, 2026.
86. Saad, Abdulrahman Muin, et al., "Rice Classification using ANN", International Journal of Academic Engineering Research (IJAER), vol. 7, no. 10, pp. 32-42, 2023.
87. Sababa, Raed Z, et al., "Classification of Dates Using Deep Learning", International Journal of Academic Information Systems Research (IJAISR), vol. 8, no. 4, pp. 18-25, 2024.
88. Salman, Fatima M, et al., "Comparative Analysis of Deep Learning Architectures for Bone Fracture Detection: MobileNetV2 vs. ResNet50", Int. J. Acad. Inf. Syst. Res.(IJAISR), vol. 10, pp. 39-51, 2026.
89. Salman, Fatima Maher, et al., "Classification of Real and Fake Human Faces Using Deep Learning", International Journal of Academic Engineering Research (IJAER), vol. 6, no. 3, pp. 1-14, 2022.
90. Taha, A, et al., "Investigating the effects of data augmentation techniques on brain tumor detection accuracy", Journal of Theoretical and Applied Information Technology, vol. 101, no. 11, pp. 9, 2023.
91. Taha, AM, et al., "A systematic literature review of deep and machine learning algorithms in brain tumor and meta-analysis", Journal of Theoretical and Applied Information Technology, vol. 101, no. 1, pp. 21-36, 2023.
92. Taha, Ashraf M, et al., "Gender Prediction from Retinal Fundus Using Deep Learning", International Journal of Academic Information Systems Research (IJAISR), vol. 6, no. 5, pp. 57-63, 2022.
93. Taha, Ashraf MH, et al., "Exploring Emotion Recognition Through EEG Brainwave Data: A Comparative Analysis of Machine Learning and Deep Learning Approaches", pp. 77-89, 2025.
94. Taha, Ashraf MH, et al., "Impact of data augmentation on brain tumor detection", Journal of Theoretical and Applied Information Technology, vol. 101, no. 11, 2023.
95. Taha, Aya Helmi Abu, et al., "Predicting Loan Defaulters: A Comprehensive Analysis and Comparative Study of Machine Learning Algorithms Using a Large-Scale Loan Default Dataset", pp. 15-28, 2025.
96. Zarandah, Qasem MM, et al., "Efficient Respiratory Disease Classification Using Customized CNN on a Large Kaggle Dataset", pp. 105-117, 2025.
97. Zarandah, Qasem MM, et al., "Machine Learning and Deep Learning Models for Respiratory Disease Prediction", vol. 2, pp. 207, 2025.
98. Zarandah, Qasem MM, et al., "Performance Evaluation of Machine Learning and Deep Learning Models for Respiratory Disease Prediction", pp. 207-218, 2024.
99. Zarandah, QM, et al., "A systematic literature review of machine and deep learning-based detection and classification methods for diseases related to the respiratory system", Journal of Theoretical and Applied Information Technology, vol. 101, no. 4, pp. 1273-1296, 2023.
100. Zarandah, QM, et al., "Spectrogram flipping: a new technique for audio augmentation", Journal of theoretical and applied information technology, vol. 101, no. 11, 2023.