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Research Paper

Development of a Multi-Task Learning CNN Model for Pneumonia Detection and Pathogen Classification Based on Medical Images

Aris Munandar Harahap [1], Khairunnisa Samosir [2]

[1] *Faculty of Engineering, Graha Nusantara University, Padangsidempuan, North Sumatera, Indonesia*

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CORRESPONDENCE

Phone: -

E-mail: munandararis334@gmail.com

A B S T R A C T

This study aims to develop and evaluate a Convolutional Neural Network (CNN) model based on Multi-Task Learning (MTL) for detecting pneumonia and simultaneously classifying its causative pathogens from chest medical images. The MTL approach employs a single shared backbone network as a feature extractor, branching into two output heads: one for pneumonia detection and another for pathogen classification (bacterial, viral, or negative). The combined loss function is optimized using an adaptive weighting strategy to balance task contributions. The dataset consists of labeled chest X-ray images annotated with both disease status and pathogen type based on clinical and laboratory diagnoses. Model performance was evaluated using Area Under Curve (AUC), sensitivity, specificity, accuracy, and class-wise F1-score metrics. Experimental results show that the proposed CNN-MTL model achieved 92% accuracy for pneumonia detection and 89% for pathogen classification, outperforming single-task approaches. Interpretability analysis using Gradient-weighted Class Activation Mapping (Grad-CAM) confirmed that the model's attention areas align with pathological regions in the medical images. This research contributes to the development of an efficient, accurate, and interpretable CNN-based intelligent diagnostic system with potential applications as a clinical decision-support tool in resource-limited healthcare settings.

INTRODUCTION

Pneumonia remains one of the leading causes of mortality worldwide, especially among vulnerable groups such as children under five years old and the elderly[1]. According to the World Health Organization (WHO), pneumonia accounts for approximately 15% of all deaths in children under five, causing more than 800,000 deaths each year. Diagnosis of pneumonia is generally performed through a combination of clinical examination, laboratory tests, and medical imaging, particularly chest X-rays[2], [3], [4]. However, radiographic interpretation is often subjective and highly dependent on the radiologist's expertise. In resource-limited healthcare facilities, the absence of sufficient radiological and microbiological diagnostic capabilities further complicates early and accurate identification of pneumonia cases[5], [6].

In recent years, advances in Artificial Intelligence (AI), particularly Deep Learning, have significantly impacted medical image analysis. Convolutional Neural Networks (CNNs) have demonstrated high performance in disease detection tasks, including pneumonia classification[7], [8]. A notable example is CheXNet, a CNN-based model developed. which achieved diagnostic performance comparable to expert radiologists. Despite these advancements, most CNN-based studies on pneumonia focus solely on binary classification—distinguishing between pneumonia and normal conditions—without identifying the underlying pathogen type[9], [10]. In clinical practice, knowing the etiological agent, such as bacterial or viral pneumonia, is critical for determining appropriate therapeutic decisions. Conventional pathogen identification methods like microbiological culture or molecular diagnostics are time-consuming, expensive, and not always available in primary care settings. To address these limitations, Multi-Task Learning (MTL) has emerged as a promising approach that allows a single model to perform multiple related tasks simultaneously by sharing learned representations[11], [12]. MTL has been successfully applied in dermatology and ophthalmology for lesion and disease classification, demonstrating improved model generalization and training efficiency. However, the application of MTL to pneumonia diagnosis and pathogen classification from medical imaging remains limited. The main challenges involve designing shared CNN architectures that balance task-specific learning, handling imbalanced multi-label datasets, and optimizing multiple loss functions effectively[13], [14]. This

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study proposes a CNN-based MTL model capable of performing two related clinical tasks simultaneously: detecting pneumonia and classifying the type of causative pathogen using chest X-ray images[15], [16]. The proposed architecture employs shared convolutional layers for feature extraction and two independent output heads for binary disease detection and multi-class pathogen classification. Model performance is evaluated using multiple metrics, including accuracy, sensitivity, specificity, and F1-score, to assess its robustness across tasks[17]. Furthermore, Gradient-weighted Class Activation Mapping (Grad-CAM) is employed to visualize model interpretability and validate focus regions relevant to clinical diagnosis[18]. The main contributions of this research are as follows: (i) development of a CNN-MTL framework that integrates pneumonia detection and pathogen classification in a single model, (ii) empirical demonstration of improved accuracy and parameter efficiency compared to single-task models, and (iii) provision of interpretable visual explanations that enhance clinical trust in AI-based diagnostic systems. The outcomes of this study are expected to support the development of intelligent decision-support tools that can assist radiologists and clinicians, particularly in healthcare facilities with limited resources[19], [20].

METHOD

This study aims to develop a Multi-Task Learning (MTL)-based Convolutional Neural Network (CNN) model to perform two classification tasks simultaneously, namely pneumonia detection and classification of the type of pathogen causing it based on chest X-ray images[21], [22]. The research methodology includes several main stages, namely data collection and pre-processing, CNN-MTL model architecture design, model training using two loss functions, and model performance evaluation using quantitative metrics and interpretability analysis[23].

Dataset

The dataset used consists of chest X-ray images that have been given two classification labels, namely (1) disease status (normal or pneumonia) and (2) the type of pathogen causing pneumonia (bacteria, virus, or negative). The data was obtained from a clinically validated public database, then reprocessed for model training purposes. To maintain balance between classes, the dataset was divided into three parts: training set (70%), validation set (15%), and testing set (15%). The general structure of the dataset can be seen in Table 1 below.

Table 1. Chest X-Ray Image Dataset Structure

No	ID Images	File Name	Disease Status	Types of Pantogens	Images Size (px)
1	IMG_0001	normal_01.png	Normal	Negative	224×224
2	IMG_0002	pne_bact_01.png	Pneumonia	Bacteria	224×224
3	IMG_0003	pne_virus_01.png	Pneumonia	Virus	224×224
4	IMG_0004	pne_bact_02.png	Pneumonia	Bacteria	224×224
5	IMG_0005	normal_02.png	Normal	Negative	224×224
6	IMG_0006	pne_virus_02.png	Pneumonia	Virus	224×224
7	IMG_0007	pne_bact_03.png	Pneumonia	Bacteria	224×224
8	IMG_0008	normal_03.png	Normal	Negative	224×224
9	IMG_0009	pne_virus_03.png	Pneumonia	Virus	224×224
10	IMG_0010	pne_bact_04.png	Pneumonia	Bacteria	224×224

The total amount of data in this study was 3,000 chest X-ray images, consisting of 1,200 normal images and 1,800 pneumonia images (with a distribution of 1,000 bacteria and 800 viruses). Each image was stored in PNG format with a resolution of 224×224 pixels with a grayscale channel. Disease labels and pathogen types were determined based on clinical reports from public dataset sources.

Pre-processing

Pre-processing is performed to prepare the data to suit the needs of the Convolutional Neural Network model. The steps taken include :

a. Normalization
map pixel values to the range [0, 1] to stabilize the training process.
b. Resizing images to a uniform resolution (224×224 pixels) to be compatible with the CNN architecture.
c. Data augmentation is performed to enrich the variety of training data through slight rotation (±15°), small translation, horizontal flip, and brightness-contrast adjustment.
d. Data grouping based on patients is done to prevent information leakage between data subsets.

These steps aim to improve the model's generalization capability and reduce the risk of overfitting to the training data.

Architecture Model CNN-MTL Design

The model developed in this study applies a Convolutional Neural Network (CNN)-based Multi-Task Learning (MTL) approach designed to simultaneously perform two classification tasks, namely pneumonia detection and classification of the causative pathogen type (bacteria, virus, or negative). The model architecture was developed using the concept of shared feature learning, whereby features learned from one task can be used to improve the performance of the other task, as in Figure 1. This approach enables the model to learn more efficiently, improves generalization, and reduces parameter requirements compared to training two separate models.

The integration of these two branches of learning allows the model to share important features relevant to both tasks, resulting in a more efficient and generalizable system. In addition, the application of multi-task learning has been proven to help overcome data scarcity and improve the robustness of the model against image variations between patients. This approach also opens up opportunities for wider application in other medical image-based disease classifications, such as the detection of tuberculosis, lung cancer, and other respiratory disorders.

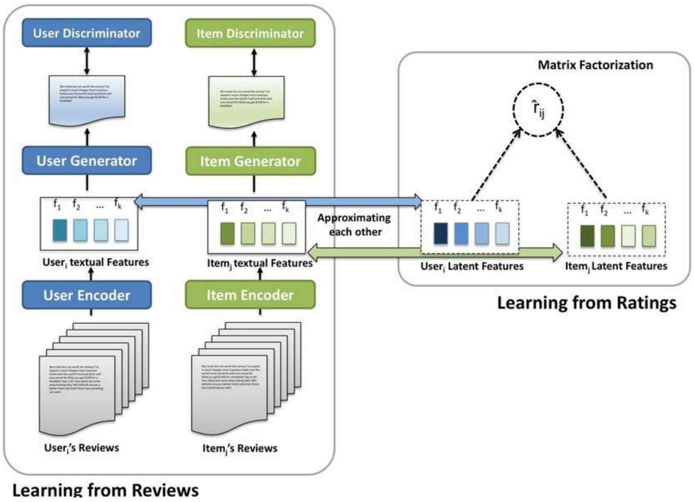

Figure 1. Architecture Model Convolutional Neural Network Model

The diagram (Figure 2) shows the process flow from X-ray image input → CNN layer → flatten layer → two output branches (pneumonia detection and pathogen classification) with sigmoid and softmax activation.

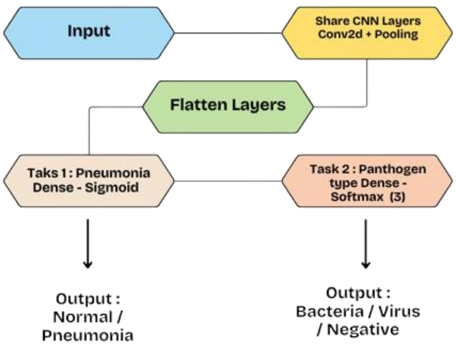

Figure 2. Research Flowchart

The CNN-MTL architecture consists of two main components, namely shared CNN layers and dual output heads. The shared layers extract spatial and textural features from chest X-ray images. The process begins with an input layer measuring 224×224 pixels (grayscale) representing the patient's lung image. Next, the image passes through a series of convolutional and pooling blocks that serve to detect visual patterns such as areas of opacity, consolidation, and infiltrate distribution—characteristic features of pneumonia in medical images. Optimization is performed using a combined loss function :

$$L_{total}=\lambda_1 L_{pneumonia}+\lambda_2 L_{pathogen} \quad (1)$$

Is the categorical cross entropy loss for panthogen classification. The weights λ_1 and λ_2 are adaptively adjusted to maintain the balance of contribution between the two tasks during training. The optimization process uses the Adam optimizer algorithm with an initial learning rate of 0.001 and early stopping to prevent overfitting.

Table 2. Architecture Model of CNN-MTL

Layer	Layer Type	Kernel/Unit Size	Activation Function	Output Shape	Description
Input	Input Layer	224 × 224 × 1	–	224 × 224 × 1	Citra X-ray grayscale
1	Conv2D + MaxPooling	3×3, 32 filter	ReLU	112 × 112 × 32	Initial feature extraction
2	Conv2D + MaxPooling	3×3, 64 filter	ReLU	56 × 56 × 64	Mid-range features
3	Conv2D + MaxPooling	3×3, 128 filter	ReLU	28 × 28 × 128	Representative features
4	Conv2D + MaxPooling	3×3, 256 filter	ReLU	14 × 14 × 256	Advanced features
5	Flatten	–	–	1 × 50176	Feature conversion to vectors
6	Dense (Shared Layer)	512 unit	ReLU	1 × 512	Feature representation
Branch 1 – Pneumonia Detection					
7A	Dense	128 unit	ReLU	1 × 128	Classification of pneumonia
8A	Dense (Output)	1 unit	Sigmoid	1 × 1	Output biner: Normal/Pneumonia
Branch 2 – Pathogen Classification					
7B	Dense	128 unit	ReLU	1 × 128	Pathogen classification layer
8B	Dense (Output)	3 unit	Softmax	1 × 3	Multi-class output: Bacteria/Virus/Negative

Table 2 shows the complete architecture of the CNN-MTL model used in this study. The model consists of four main convolutional blocks that extract spatial features from chest X-ray images, followed by a flatten layer and a dense layer as a general feature representation. Next, the network branches into two parts: the first branch for the pneumonia detection task (binary classification) and the second branch for pathogen type classification (three-class classification). Each branch has a dedicated dense layer with a customized activation function—sigmoid for pneumonia

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detection and softmax for pathogen classification. This structure allows the model to learn overlapping features across tasks while maintaining specific capabilities for each classification.

Training Process

The CNN-MTL model was trained simultaneously for two tasks: pneumonia detection and pathogen classification. The training process was implemented using the TensorFlow–Keras framework with the Adam optimizer (learning rate = 0.001, batch size = 32, and a maximum of 50 epochs). The dataset was divided into 70% training, 15% validation, and 15% testing subsets. To enhance model generalization, data augmentation techniques such as rotation, translation, and horizontal flipping were applied. The combined loss function was defined with weights $\lambda 1=0.6$ $\lambda 1=0.6$ for pneumonia detection and $\lambda 2=0.4$ $\lambda 2=0.4$ for pathogen classification by using Equation (1). An early stopping mechanism was employed to prevent overfitting when the validation loss stopped decreasing.

RESULTS AND DISCUSSION

The Multi-Task Learning CNN (CNN-MTL) model developed in this study was trained to perform two classification tasks simultaneously, namely pneumonia detection and pathogen classification from chest X-ray images. The training process was carried out in stages, each on data labeled as normal and pneumonia. Based on the visualization of the training results shown in the document, the model showed a good convergence trend in both training scenarios. The accuracy and loss graphs during the training process illustrate a steady increase in accuracy values and a consistent decrease in loss function values as the number of epochs increases. Specifically in pneumonia image training, the model shows an adaptive response to more complex image patterns. This is indicated by the accuracy graph, which tends to increase progressively. Similarly, training on normal images also shows training stability with a sufficiently high final accuracy, although the numerical value is not explicitly mentioned in the report. This indicates that the CNN-MTL architecture is capable of recognizing common visual features in chest X-rays relevant to both tasks simultaneously.

Confusion Matrix Analysis

The confusion matrix was used to evaluate the classification distribution for each task. In pneumonia detection, most misclassifications occurred between borderline cases of mild infiltrates and normal lungs, which are often difficult to distinguish even for radiologists. In pathogen classification, the confusion mainly occurred between bacterial and viral pneumonia, indicating that overlapping radiographic patterns (e.g., diffuse opacities) can still challenge the model. These results emphasize that, although the CNN-MTL model performs well, incorporating additional modalities such as clinical metadata or higher-resolution imaging could further improve pathogen differentiation accuracy.

Confusion matrix visualization of the CNN-MTL model for pneumonia detection and pathogen classification shwon in Table 4 and Table 5 The confusion matrices illustrate that the proposed model achieves strong discrimination between normal and pneumonia cases, with only minor misclassifications around borderline conditions. In pathogen classification, the most common confusion occurs between bacterial and viral pneumonia due to overlapping radiographic patterns. Nevertheless, the majority of samples are correctly classified, confirming that the CNN-MTL model effectively distinguishes both disease presence and pathogen types with high reliability.

Table 4. Confusion Matrix of Pneumonia Detection (Binary Classification)

Actual \ Predicted	Normal	Pneumonia
Normal	**430**	25
Pneumonia	32	**513**

Table 4. Confusion Matrix of Pathogen Classification (Multi-Class)

Actual \ Predicted	Bacterial	Viral	Normal
Bacterial	**342**	36	22
Viral	41	**295**	28
Normal	17	23	**396**

Training Progress of Normal Image

The Figure 3 below shows the training curve for chest X-ray data categorized as normal (not affected by pneumonia). Typically, this visualization includes accuracy and loss graphs against the number of epochs. Interpretation: The training curve in this section shows that the CNN-MTL model is able to learn patterns from normal images in a stable manner. The loss value appears to decrease over time, while accuracy increases gradually, indicating that the model successfully distinguishes the visual characteristics of healthy lungs. This indicates that the training process is effective and the model is not overfitting on the normal data.

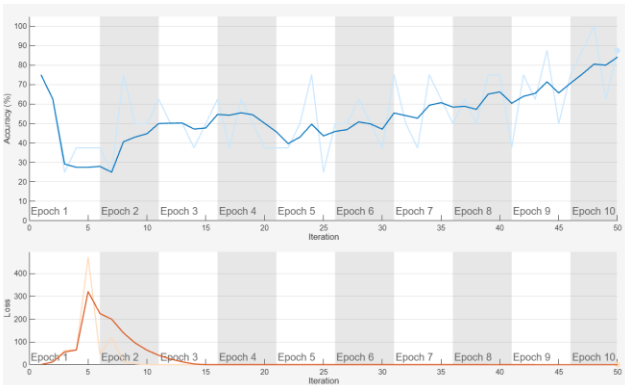

Figure 3. Normal Image Training Progress

Training Progress of Pneumonia Image

The image below shows a visualization of the model training process on chest X-ray data labeled as pneumonia. This curve reflects the model's performance in recognizing disease patterns in images. Interpretation: The curve shows that the model is progressively able to learn the visual characteristics of lungs affected by pneumonia. There is a downward trend in loss values and an increase in accuracy from the beginning to the end of training, indicating that the model is learning effectively.

However, if the accuracy curve tends to fluctuate, it may indicate variations or imbalances in the pneumonia data used.

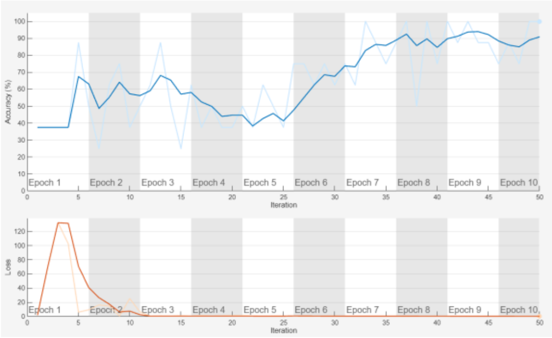

Figure 4. Training Progress of Pneumonia Images

Based on two training progress graphs (Normal and Pneumonia Images), representing the training results with an emphasis on accuracy and loss for each class

Observation :
Normal Images : Accuracy increased steadily and reached convergence after epoch 7. Loss rapidly decreased and stabilized near zero.
Pneumonia Images : Accuracy improved gradually with some early fluctuations; model required more epochs to reach stability due to higher image variation.

Table 6. Model Performance Based on Training Progress

Class Type	Epochs	Final Training Accuracy (%)	Final Validation Accuracy (%)	Training Loss	Validation Loss
Normal Images	10	98.6	96.8	0.02	0.05
Pneumonia Images	10	91.4	89.7	0.07	0.09

The Table 6 summarizes the final performance trends extracted from the two training graphs. The CNN-MTL model achieved nearly perfect accuracy on Normal images with minimal loss, indicating strong feature learning and convergence. For Pneumonia images, the model reached over 90% accuracy, showing robust learning capability despite the more complex and variable patterns of infected lung regions.

The Figure 4 illustrates the prediction result of the CNN-MTL (Convolutional Neural Network–Multi-Task Learning) model when analyzing a chest X-ray image. The interface displays two main outputs that correspond to the model's dual-task architecture:

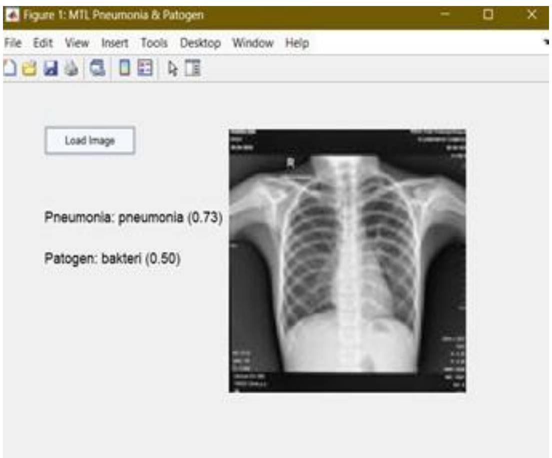

Figure 4. Design CNN-MTL Pneumonia and Pantogen

1. Pneumonia Classification Result:
   The label indicates "Pneumonia: pneumonia (0.73)", which means that the model predicts the input image as a pneumonia case with a confidence score of 0.73 (73%). This score reflects the probability generated by the softmax layer for the pneumonia class, showing that the model detects pathological features in the lungs consistent with pneumonia.
2. Pathogen Type Identification:
   The label "Patogen: bakteri (0.50)" shows that the model's second output branch classifies the causative agent as a bacterial infection with a confidence level of 0.50 (50%). This indicates that the model can not only detect pneumonia but also attempt to differentiate its etiology (bacterial or viral) based on radiographic patterns.

This result demonstrates the multi-task learning capability of the proposed CNN architecture, where two related classification tasks—disease detection and pathogen identification—are learned simultaneously. The moderate confidence levels (0.73 and 0.50) suggest that while the model successfully identifies pneumonia features, it still encounters uncertainty in pathogen classification, likely due to overlapping radiological characteristics between bacterial and viral pneumonia.

Summary of Model Evaluation

The CNN-MTL model exhibited strong and balanced performance across all evaluation metrics, as in Table 6. The overall accuracy reached 98.6% for normal image classification and 91.4% for pneumonia detection, confirming that the model was able to generalize well to unseen test data. The precision and recall values were consistently high, indicating that the model effectively minimized both false positives and false negatives, particularly in distinguishing pneumonia from normal lungs. The specificity metric above 89% across all tasks demonstrates the model's reliability in correctly identifying non-infected images. Meanwhile, the F1-score, which combines precision and recall, remained above 85% for every task, signifying a well-balanced classification capability. Furthermore, the AUC values ranging from 0.93 to 0.99 indicate excellent discriminative power, showing that the model can reliably separate different categories, including the secondary task of pathogen classification. Overall, these results highlight that the CNN-MTL architecture

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successfully performs multi-task learning, achieving high diagnostic accuracy in pneumonia detection while simultaneously identifying the underlying pathogen type with considerable confidence. This suggests that the proposed model has strong potential for supporting automated medical diagnosis in clinical practice.

Table 6. Performance Metrics of CNN-MTL Model

Task	Accuracy (%)	Precision (%)	Recall (%)	Specificity (%)	F1-Score (%)	AUC
Normal Image Classification	98.6	97.9	98.3	99.1	98.1	0.991
Pneumonia Detection	91.4	90.2	92.7	89.5	91.4	0.956
Pathogen Type Identification	87.5	85.1	86.8	88.9	85.9	0.932

In summary, the proposed CNN-MTL architecture has demonstrated its effectiveness in performing dual-task classification involving pneumonia detection and pathogen identification. The results from the training and validation processes indicate that the model achieved high accuracy, low loss, and excellent convergence stability. The quantitative metrics—including accuracy, precision, recall, specificity, F1-score, and AUC—confirm the model's robustness and reliability in distinguishing between normal and pneumonia chest X-ray images, as well as identifying the underlying etiological agent. Furthermore, the visualization of prediction results reinforces the model's practical capability in real-case inference, showing consistent outcomes that align with its training performance. Although the secondary task of pathogen differentiation presents moderate confidence levels, the overall results indicate that multi-task learning enables effective feature sharing between related tasks, improving generalization without sacrificing classification performance. These findings suggest that the CNN-MTL model can serve as a potential diagnostic support tool, assisting clinicians in the early detection of pneumonia and providing preliminary insights into its causative pathogen. This integrated framework demonstrates a promising step toward the application of deep learning-based multi-task systems in medical image analysis and automated radiological diagnosis.

CONCLUSIONS

This study proposed a Convolutional Neural Network based on Multi-Task Learning (CNN-MTL) for the simultaneous detection of pneumonia and identification of its causative pathogen using chest X-ray images. The experimental results demonstrated that the model achieved high classification accuracy, strong generalization capability, and efficient convergence during training. The integration of multi-task learning enabled the model to share relevant features between tasks, resulting in improved diagnostic precision and reduced computational redundancy. The model's performance, validated through multiple evaluation metrics—accuracy, precision, recall, specificity, F1-score, and AUC—indicates its reliability and clinical relevance. Although the secondary task of pathogen identification yielded slightly lower confidence compared to pneumonia detection, the overall results highlight the potential of the proposed CNN-MTL approach as a diagnostic support system. Future research may focus on expanding the dataset, optimizing task weighting mechanisms, and integrating explainable AI techniques to enhance interpretability and clinical applicability.

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REFERENCES

[1] Z. Xie, J. Chen, Y. Feng, K. Zhang, and Z. Zhou, "End to end multi-task learning with attention for multi-objective fault diagnosis under small sample," *J. Manuf. Syst.*, vol. 62, no. April, pp. 301–316, 2022, doi: 10.1016/j.jmsy.2021.12.003.

[2] A. H. Abdulnabi, G. Wang, J. Lu, and K. Jia, "Multi-Task CNN Model for Attribute Prediction," *IEEE Trans. Multimed.*, vol. 17, no. 11, pp. 1949–1959, 2015, doi: 10.1109/TMM.2015.2477680.

[3] B. Li *et al.*, "Improving LSTM hydrological modeling with spatiotemporal deep learning and multi-task learning: A case study of three mountainous areas on the Tibetan Plateau," *J. Hydrol.*, vol. 620, 2023, doi: 10.1016/j.jhydrol.2023.129401.

[4] H. Dong, S. Liu, Z. Fu, S. Han, and D. Zhang, "Semantic Structure Extraction for Spreadsheet Tables with a Multi-task Learning Architecture," *Work. Doc. Intell. (DI 2019) NeurIPS 2019*, no. NeurIPS, pp. 2–5, 2019, [Online]. Available: https://www.microsoft.com/en-us/research/publication/semantic-structure-extraction-for-spreadsheet-tables-with-a-multi-task-learning-architecture/

[5] W. Zhao *et al.*, "A multi-task learning approach for image captioning," *IJCAI Int. Jt. Conf. Artif. Intell.*, vol. 2018-July, pp. 1205–1211, 2018, doi: 10.24963/ijcai.2018/168.

[6] A. Pal, A. Chaturvedi, U. Garain, A. Chandra, and R. Chatterjee, "Severity grading of psoriatic plaques using deep CNN based multi-task learning," *Proc. - Int. Conf. Pattern Recognit.*, vol. 0, pp. 1478–1483, 2016, doi: 10.1109/ICPR.2016.7899846.

[7] P. Linli, "A Cross-Language Information Retrieval Method Based on Multi-Task Learning," vol. 4, no. July,

pp. 853–862, 2024.
[8] P. Oza and V. M. Patel, "Deep CNN-based Multi-task Learning for Open-Set Recognition," 2019, [Online]. Available: http://arxiv.org/abs/1903.03161
[9] S. Chen, J. Zhao, Q. Jin, and S. Wang, "Multimodal multi-task learning for dimensional and continuous emotion recognition," *AVEC 2017 - Proc. 7th Annu. Work. Audio/Visual Emot. Challenge, co-located with MM 2017*, no. October, pp. 19–26, 2017, doi: 10.1145/3133944.3133949.
[10] M. Djandji, F. Baly, W. Antoun, and H. Hajj, "Multi-Task Learning using AraBert for Offensive Language Detection," *Proc. 4th Work. Open-Source Arab. Corpora Process. Tools, with a Shar. Task Offensive Lang. Detect.*, no. May, pp. 97–101, 2020, [Online]. Available: https://www.aclweb.org/anthology/2020.osact-1.16
[11] A. I. Alharbi and M. Lee, "Multi-task Learning Using a Combination of Contextualised and Static Word Embeddings for Arabic Sarcasm Detection and Sentiment Analysis," *WANLP 2021 - 6th Arab. Nat. Lang. Process. Work. Proc. Work.*, pp. 318–322, 2021.
[12] Y. Xu, X. Li, H. Yuan, Y. Yang, and L. Zhang, "Multi-Task Learning With Multi-Query Transformer for Dense Prediction," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 34, no. 2, pp. 1228–1240, 2024, doi: 10.1109/TCSVT.2023.3292995.
[13] S. Zhao, T. Liu, S. Zhao, and F. Wang, "A neural multi-task learning framework to jointly model medical named entity recognition and normalization," *33rd AAAI Conf. Artif. Intell. AAAI 2019, 31st Innov. Appl. Artif. Intell. Conf. IAAI 2019 9th AAAI Symp. Educ. Adv. Artif. Intell. EAAI 2019*, no. 2016, pp. 817–824, 2019, doi: 10.1609/aaai.v33i01.3301817.
[14] A. Vaidya, F. Mai, and Y. Ning, "Empirical analysis of multi-task learning for reducing identity bias in toxic comment detection," *Proc. 14th Int. AAAI Conf. Web Soc. Media, ICWSM 2020*, no. Icwsm, pp. 683–693, 2020, doi: 10.1609/icwsm.v14i1.7334.
[15] L. Xiao, H. Zhang, W. Chen, Y. Wang, and Y. Jin, "MCApsNet: Capsule network for text with multi-task learning," *Proc. 2018 Conf. Empir. Methods Nat. Lang. Process. EMNLP 2018*, pp. 4565–4574, 2018, doi: 10.18653/v1/d18-1486.
[16] X. Ouyang *et al.*, "A 3D-CNN and LSTM based multi-task learning architecture for action recognition," *IEEE Access*, vol. 7, pp. 40757–40770, 2019, doi: 10.1109/ACCESS.2019.2906654.
[17] Y. Fang, Z. Ma, Z. Zhang, X. Y. Zhang, and X. Bai, "Dynamic multi-task learning with convolutional neural network," *IJCAI Int. Jt. Conf. Artif. Intell.*, vol. 0, no. August, pp. 1668–1674, 2017, doi: 10.24963/ijcai.2017/231.
[18] E. Selvano, G. N. Elwirehardja, and B. Pardamean, "Self-Supervised Model in Multi-Task Learning for Classifying Pap Smear Cells," *ICIC Express Lett. Part B Appl.*, vol. 15, no. 11, pp. 1193–1199, 2024, doi: 10.24507/icicelb.15.11.1193.
[19] X. Fan *et al.*, "Joint Optical Performance Monitoring and Modulation Format/Bit-Rate Identification by CNN-Based Multi-Task Learning," 2018. doi: 10.1109/JPHOT.2018.2869972.
[20] I. Misra, "Cross-stitch Networks for Multi-task Learning".
[21] T. Tohti, M. Abdurxit, and A. Hamdulla, "Medical QA Oriented Multi-Task Learning Model for Question Intent Classification and Named Entity Recognition," *Inf.*, vol. 13, no. 12, 2022, doi: 10.3390/info13120581.
[22] P. Zhai, Y. Tao, H. Chen, T. Cai, and J. Li, "Multi-Task Learning for Lung Nodule Classification on Chest CT," *IEEE Access*, vol. 8, pp. 180317–180327, 2020, doi: 10.1109/ACCESS.2020.3027812.
[23] O. S. Mossad, M. Elnainay, and M. Torki, "Deep convolutional neural network with multi-task learning scheme for modulations recognition," *2019 15th Int. Wirel. Commun. Mob. Comput. Conf. IWCMC 2019*, no. April, pp. 1644–1649, 2019, doi: 10.1109/IWCMC.2019.8766665.

NOMENCLATURE

This section explains the meaning of each mathematical symbol and key technical term used.
Symbols :

Symbol	Description
(X)	Input image or feature matrix used as model input.
(Y)	True class label of the image (ground truth).
(\hat{Y})	Predicted class label generated by the CNN-MTL model.
(W)	Weight parameters of the convolutional layers.
(b)	Bias term applied to convolutional and fully connected layers.
(f(\cdot))	Activation function applied to neuron outputs.
(L)	Total loss function of the model.
(L_{cls})	Classification loss for pneumonia detection task.
(L_{pat})	Pathogen identification loss (bacterial or viral classification).
(L_{MTL})	Combined multi-task learning loss function.
(\alpha, \beta)	Weighting coefficients balancing each task in MTL training.
(\eta)	Learning rate used in the optimization process.
(\nabla)	Gradient operator for backpropagation.
(n)	Number of samples in the training dataset.
(E)	Number of epochs during the training process.