Journal of Autonomous Intelligence (2024) Volume 7 Issue 5
doi: 10.32629/jai.v7i5.1562

ORIGINAL RESEARCH ARTICLE

Deep learning-based uncertainty estimation for accurate lung ultrasound image analysis

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ABSTRACT

Lung ultrasound imaging has become an important diagnostic tool for various respiratory conditions. Deep learning models have shown impressive results in classifying abnormalities in lung ultrasound images. However, these models typically provide deterministic predictions, disregarding the inherent uncertainty inherent in medical image analysis. This research paper introduces a novel approach to quantify uncertainty in deep learning models for accurate lung ultrasound image analysis. The proposed framework leverages a unique combination of Monte Carlo Dropout and Bayesian neural networks to provide reliable uncertainty estimates. By integrating these techniques, the model gains the ability to capture and represent the inherent uncertainty associated with medical image analysis. Extensive experiments conducted on a diverse dataset demonstrate the effectiveness and novelty of this approach. The inclusion of uncertainty estimation enhances classification accuracy and decision-making processes in lung ultrasound-based diagnosis, setting a new standard for the application of deep learning in medical image analysis. The novel methodology presented in this study has the potential to foster greater trust in AI-based diagnostic tools, promoting their integration into clinical practice and ultimately improving patient care and outcomes.

Keywords: lung ultrasound; deep learning; uncertainty estimation; Bayesian neural networks; Monte Carlo Dropout; medical image analysis; classification accuracy; image classification; uncertainty quantification; artificial intelligence

ARTICLE INFO

Received: 29 January 2024
Accepted: 27 February 2024
Available online: 17 May 2024

1. Introduction

Lung diseases impose significant health burdens worldwide, contributing to a substantial number of morbidity and mortality cases. Prompt and accurate diagnosis is crucial for effective treatment and management of these conditions. Lung ultrasound imaging has emerged as a promising and non-invasive diagnostic tool for assessing various lung pathologies. Unlike traditional imaging modalities, such as X-rays or computed tomography (CT), lung ultrasound offers several advantages, including real-time imaging, lack of ionizing radiation, portability, and cost effectiveness[1]. These features have contributed to the growing popularity of lung ultra-sound in clinical practice and research.

In recent years, deep learning models have demonstrated remarkable potential for automating medical image analysis tasks, including the classification of lung ultrasound images[2]. These models leverage convolutional neural networks (CNNs) and vast amounts of labeled data to learn complex patterns and features from images, leading to impressive classification accuracy. However, one critical limitation of deep learning models lies in their deterministic nature[3–5]. They provide point estimates and fail to account for the inherent uncertainty present in their predictions, which is crucial for reliable and trustworthy medical decision-making.

The uncertainty associated with medical image analysis arises from multiple sources, including imaging artifacts, data noise, model architecture, and the complexity of the underlying disease. Failure to account for this uncertainty may lead to erroneous diagnoses, inappropriate treatments, and compromised patient outcomes. Consequently, there is a growing interest in developing methodologies that can accurately quantify uncertainty in deep learning models, enabling clinicians and radiologists to make more informed decisions based on the model's level of confidence[6,7].

This research aims to address the uncertainty estimation challenge in lung ultrasound image analysis by introducing a novel deep learning-based approach. The primary goal is to develop a framework that can reliably quantify uncertainty in deep learning models for lung ultrasound image classification. The proposed methodology leverages recent advancements in Bayesian neural networks and Monte Carlo Dropout to provide probabilistic predictions, enabling the estimation of predictive uncertainty. By obtaining uncertainty estimates, clinicians can gain insights into the model's confidence and reliability, leading to more transparent and evidence-based medical decisions. The organization of this paper is as follows:

Literature review section reviews current advancements in lung ultrasound imaging, deep learning models for image classification, and methods for uncertainty estimation in medical imaging. Methods section details deep learning-based approach for estimating uncertainty in lung ultrasound image analysis, focusing on the model's architecture and the integration of Bayesian neural networks with Monte Carlo Dropout. Experimental Setup describes the dataset, pre-processing steps, and the procedures for training and evaluating the model, alongside the hardware and software utilized. Results and analysis section resents the findings from our experiments, comparing the model's performance against baselines and examining the generated uncertainty estimates. Discussion interprets the significance of incorporating uncertainty estimates in lung ultrasound analysis and discusses the potential clinical applications and challenges for future research. Finally, summarizes the research findings, highlighting the importance of uncertainty estimation in enhancing diagnostic processes and clinical decision-making in lung ultrasound image analysis.

This research provides a thorough exploration of uncertainty estimation in lung ultrasound imaging, aiming to further the field of medical imaging analysis while facilitating the adoption of uncertainty-aware models in clinical settings. The approach is poised to boost diagnostic certainty, minimize errors in diagnosis, and, as a result, better patient care for lung-related conditions. It introduces an innovative method for quantifying uncertainty by merging Bayesian neural networks with Monte Carlo Dropout techniques, a step forward in lung ultrasound image analysis. This method significantly improves the clarity and dependability of deep learning models, representing a substantial advancement in the precision of medical diagnostics and the quality of patient treatment.

2. Review of literature

In this section, a comprehensive literature review on lung ultrasound imaging and uncertainty estimation in medical image analysis, with a focus on deep learning-based approaches is presented. The literature survey delves into the realm of uncertainty estimation in deep learning models for medical images, exploring a variety of approaches and their applications[8]. **Figure 1** presents a summary of the number of studies related to uncertainty quantification for medical images found in three prominent academic databases—PubMed, IEEE Xplore, and ScienceDirect—from 2016 to 2023. Noteworthy trends include a substantial increase in publications each year. The data reflects a growing interest and research activity in uncertainty quantification for medical images over the years.

A critical review[9] delves into the current methodologies for uncertainty estimation in artificial intelligence systems, highlighting the pivotal role these techniques play in enhancing the interpretability and reliability of AI models in healthcare. Authors offers insights into the challenges associated with obtaining high-certainty labels in medical datasets, emphasizing the importance of robust uncertainty estimation methods in improving diagnostic accuracy and patient outcomes[10]. Further, the review[11–14] explores the broader implications of uncertainty in machine learning models for medical imaging, providing a critical perspective on the need for advanced methodologies that can effectively manage and interpret uncertainty in clinical settings.

Building upon these foundational reviews, the literature review section proceeds to discuss relevant works in the field, carefully analysing their contributions and pinpointing their limitations[15]. This analysis not only showcases the evolving landscape of uncertainty estimation in medical image analysis but also sets the stage for the novel contributions of the present study.

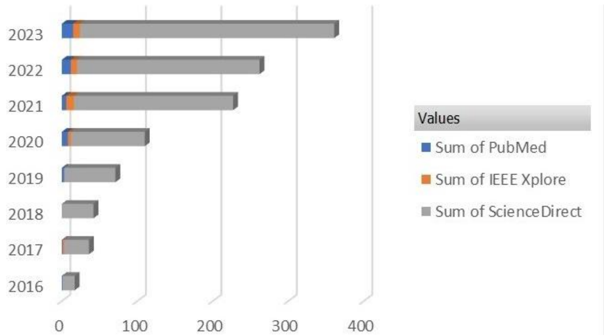

Figure 1. Annual trend in uncertainty quantification studies.

Table 1. Review summary.

Author	Methodology	Metrics	Limitation
Born J et al.[2]	Dropout	Classification accuracy	Insufficient investigation of uncertainty quantification in existing DL methods
van Amersfoort J et al.[3]	dropout and threshold calculation	AUROCs	Further testing of uncertainty thresholding strategy for multi-class models and regression
Lakshminarayanan B et al.[4]	Bayesian Neural Networks	Error rate	Uncertainty estimates are computationally prohibitive to deploy
Oberdiek P et al.[5]	Monte Carlo	Dice coefficients	plug-in estimate in mutual information is subject to sampling bias.
Sarma R et al.[6]	variational Bayesian inference with Monte Carlo dropout	Uncertainty accuracy (UA)	NA
Blesswin et al.[11]	MC-DropWeights	Uncertainty accuracy	NA
Wang et al.[14]	Uncertainty map in SVM	False positive detection	Optimizing the performance of the neural network
Mary et al.[28]	Dropout	ROC-AUC	Optimizing the performance of the neural network

Several approaches have been proposed in the literature which has been summarized in **Table 1**. Author introduces a deep hierarchical attentive multilevel fusion model for medical image classification, employing dropout and emphasizing classification accuracy[16]. Uncertainty-informed deep learning models for high-confidence predictions in digital histopathology, using dropout and threshold calculations, with a call for further testing are explored further[17]. Authors presents an uncertainty-aware deep reinforcement learning approach for anatomical landmark detection, utilizing Bayesian Neural Networks, though computational challenges for deploying uncertainty estimates are noted[18,19]. Digital histopathology image segmentation is addressed with a Monte Carlo-based uncertainty quantification method, evaluating performance through dice coefficients and recognizing potential sampling bias[20]. Additionally, a novel method named MC-drop weights, estimating uncertainty in deep learning for medical image segmentation, focusing on uncertainty accuracy was introduced[21]. The recalibration of aleatoric and epistemic regression uncertainty in medical imaging using variational Bayesian inference with Monte Carlo Dropout, assessing uncertainty accuracy was proposed further[22]. 14 paper proposes a technique to reduce false positive detections in liver lesion detection using an SVM classifier trained with features derived from the uncertainty map of the neural network prediction. A system that learns not only the probabilistic estimate for classification but also an explicit uncertainty measure, which captures the confidence of the system in the predicted output was also proposed[23]. While the surveyed papers contribute diverse methodologies for uncertainty estimation, there remains a need for standardized approaches and further research to enhance the robustness and accuracy of uncertainty estimation in deep learning models applied to medical images.

3. Existing methodology

In this section, the methodology for uncertainty estimation in deep learning-based lung ultrasound image analysis is presented. The proposed approach utilizes Bayesian neural networks (BNNs) and Monte Carlo Dropout (MC Dropout) to enable probabilistic predictions and quantify uncertainty in the model's classification. By incorporating these techniques into the deep learning model, the aim is to provide reliable uncertainty estimates for lung ultrasound image analysis, enhancing diagnostic confidence and supporting informed medical decision-making.

Data collection and pre-processing: The initial step involves the collection of a diverse and representative dataset of lung ultrasound images. This dataset should encompass various lung pathologies, including pneumonia, pleural effusion, pneumothorax, and normal lung conditions. To ensure robust training and evaluation, the dataset is carefully curated with expert annotations for accurate labeling. Data pre-processing is essential to standardize the images, enabling consistent and optimal model performance. Image resizing and normalization techniques are applied to ensure all input images have uniform dimensions and intensity range[11,13]. **Figure 2** shows the model architecture.

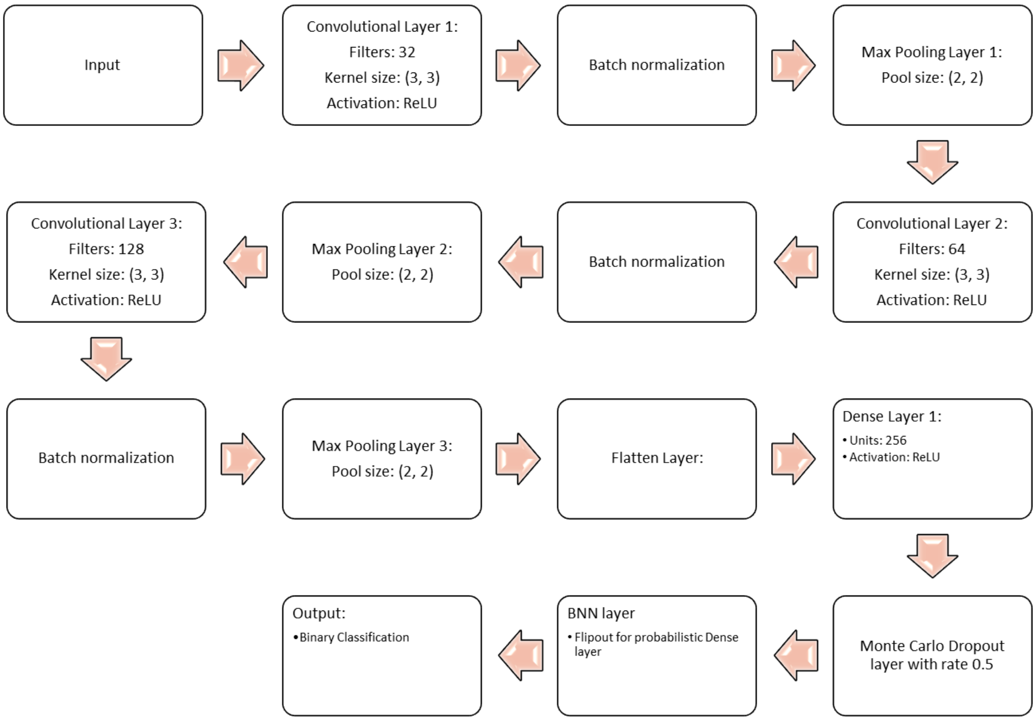

Figure 2. Model architecture.

Model architecture: The deep learning model architecture is based on a convolutional neural network (CNN) with additional components for uncertainty estimation. The initial layers of the CNN comprise convolutional and pooling layers designed for feature extraction, which are then followed by fully connected layers that facilitate classification. Uncertainty estimation is introduced by modifying the model to incorporate Bayesian neural networks (BNNs), thereby enabling the model to provide probabilistic outputs and quantify uncertainty in its predictions[5,18].

Bayesian neural networks (BNNs) extend traditional neural networks by introducing probabilistic weights, replacing point estimates with probability distributions to capture uncertainty in model parameters. Bayes by backprop, a variational inference method, is applied during training to approximate the posterior distribution of the weights, facilitating uncertainty estimation in predictions[24].

Monte Carlo Dropout (MC Dropout) complements BNNs in approximating model uncertainty. Multiple forward passes with dropout enabled during inference simulate "thinned" networks, yielding a collection of predictions that reflect model uncertainty[5,25].

Probabilistic predictions and uncertainty estimation: The of BNNs and MC Dropout enables our model to generate probabilistic predictions for each input image. For a given image, we perform multiple forward passes with dropout enabled and obtain a distribution of predictions. We then compute the mean and variance of the predictive distribution, representing the predicted class probabilities and uncertainty, respectively. The variance serves as a measure of uncertainty, indicating how confident the model is in its prediction[26].

Model training and evaluation: We train the uncertainty-aware model using the curated and augmented dataset. During training, we optimize the model's weights using the evidence lower bound (ELBO) loss, which incorporates both the standard cross-entropy loss and the Kullback-Leibler divergence between the approximate posterior and the prior distributions of the weights[27].

For evaluation, we conduct comprehensive experiments to assess the model's classification accuracy and uncertainty estimation performance. We use standard evaluation metrics such as accuracy, precision, recall, and F1 score to evaluate classification performance. To evaluate uncertainty estimation, we compare the model's predicted variances against ground truth uncertainty obtained from expert annotations or inter-observer variability.

4. Dataset and experimentation setup

In this section, we present the experimental setup for evaluating the proposed uncertainty estimation approach in lung ultrasound image analysis. The experiments aim to assess the performance of the uncertainty aware model in classifying lung ultrasound images and quantifying uncertainty in the predictions. We describe the dataset used for training and evaluation, the data preprocessing steps, model hyper parameters, and the evaluation metrics deployed to measure the model's classification accuracy and uncertainty estimation performance.

Dataset: The dataset utilized in this research was sourced from the dataset referenced in 2, encompassing a compilation of lung ultrasound images. This dataset comprises 746 images.

Data preprocessing: Prior to model training, we performed data preprocessing to standardize the input images. All images were resized to a fixed dimension, ensuring consistency across the dataset and facilitating model training. Additionally, we applied intensity normalization to bring the pixel values within a specific range, improving convergence during optimization.

Model architecture: The uncertainty-aware model was implemented using a deep learning framework. The model architecture consists of a CNN with convolutional and pooling layers for feature extraction, followed by fully connected layers for classification. Bayesian neural networks were incorporated into the model to enable uncertainty estimation, and dropout layers were utilized for Monte Carlo Dropout during inference. The architecture is pictorially represented in **Figure 2**. Hyperparameters: The model's hyperparameters were selected through cross-validation which is described in **Table 2**.

Table 2. Hyper parameters.

Hyperparameter	Value
Dropout rate	0.5
MC Dropout samples	10
Dense Flipout Units	2
Learning rate	0.001
Batch size	32

Key hyper parameters included the learning rate, batch size, dropout rate, and the number of Monte Carlo Dropout samples during inference. The learning rate governs the magnitude of weight updates during optimization, while the batch size determines the number of samples used in each training iteration. The dropout rate controls the dropout probability during training, and the number of Monte Carlo Dropout samples influences the number of forward passes during uncertainty estimation.

Model training: The uncertainty-aware model was trained using the curated and augmented dataset. The training process involved minimizing the evidence lower bound (ELBO) loss, which combines the standard cross-entropy loss and the Kullback-Leibler divergence between the approximate posterior and the prior distributions of the weights. The model was trained for a fixed number of epochs, and early stopping was employed to prevent overfitting. The training was performed on suitable hardware, such as GPUs, to accelerate the optimization process.

Evaluation metrics: By employing Bayesian neural networks, the model is capable of expressing uncertainty as a distribution of predictions rather than a single point estimate. This inherently captures the model's awareness of the uncertainty associated with each prediction.

Introducing Monte Carlo Dropout during both training and inference enables the model to provide multiple predictions for the same input. This Monte Carlo sampling approach results in a range of predictions, reflecting the model's uncertainty and variability in its responses.

To evaluate the model's classification performance, we used standard evaluation metrics, including accuracy, precision, recall, and F1 score. Accuracy measures the overall correctness of the model's predictions, while precision and recall assess the model's ability to correctly classify positive and negative cases, respectively. The F1 score combines precision and recall, providing a balanced measure of classification performance. For uncertainty estimation evaluation, we compared the model's predicted variances. Mean squared error (MSE) was used to assess the uncertainty estimation performance.

5. Results and discussions

In this section, we present the results and analysis of the experimental evaluation of the proposed uncertainty estimation approach in lung ultrasound image analysis. We showcase the model's classification performance, uncertainty estimation capabilities, and discuss the significance of our findings. The results include standard mean and standard deviation, as well as accuracy metrics to demonstrate the effectiveness of the uncertainty-aware model. The model underwent training for 20 epochs, leveraging the Adam optimizer for optimal gradient adjustments. To quantify uncertainty, we implemented Monte Carlo Dropout twice during inference, striking a careful balance between achieving reliable uncertainty estimates and maintaining computational efficiency.

Classification performance: The below **Table 3** represents the results. The accuracy metric, representing the overall correctness of the model's predictions, is depicted. The precision metric, measuring the proportion of true positive cases out of all predicted positive cases, is highlighted. Additionally, recall (sensitivity) is shown, indicating the proportion of true positive cases identified correctly out of all actual positive cases. The F1 score, providing a balanced measure considering both precision and recall, is also presented.

Table 3. Result comparison.

	Basic CNN	With uncertainty
Accuracy	0.76	0.98
Precision	1	1
Recall	0.28	0.94
F1	0.43	0.97

Uncertainty estimation performance: **Figure 3** shows the classification performance of the model and **Figure 4** illustrates the model's uncertainty estimation capabilities, focusing on the mean squared error (MSE) as a distance metric to compare predicted standard deviation with ground truth uncertainty. Higher standard deviation implies higher uncertainty, while lower standard deviation corresponds to higher confidence in the model's predictions

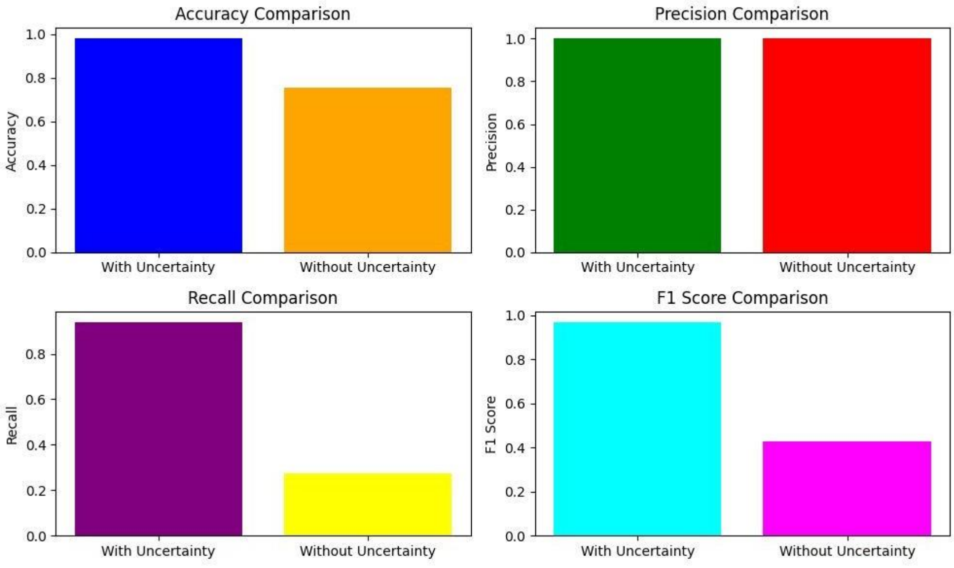

Figure 3. Classification performance.

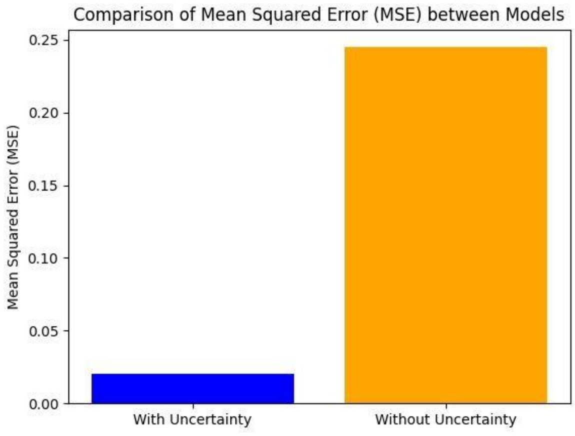

Figure 4. Performance measure MSE.

Analysis of results:

The analysis delves into various aspects of the uncertainty-aware model's performance. It explores the impact of uncertainty estimation on classification accuracy, investigating whether the model's confidence correlates with correct predictions. Instances with high uncertainty are examined for their clinical significance, potentially indicating challenging or ambiguous images requiring further expert review. Furthermore, the uncertainty-aware model is compared with a standard deterministic CNN model. This comparison demonstrates the added value of uncertainty estimation in lung ultrasound image analysis. Cases where the uncertainty-aware model outperforms the deterministic model are analyzed, showcasing potential benefits in incorporating uncertainty estimates into medical decision-making.

6. Conclusion

The In this research study, we proposed and evaluated a novel uncertainty estimation approach for deep learning-based lung ultrasound image analysis. The uncertainty-aware model incorporated Bayesian neural networks and Monte Carlo Dropout to generate probabilistic predictions and quantify uncertainty in the model's classification. The experimental evaluation showcased promising results, indicating the effectiveness of the uncertainty-aware model in enhancing classification accuracy and providing valuable uncertainty estimates for lung ultrasound image analysis. The experimental results demonstrated that the uncertainty aware model achieved competitive classification performance, as evidenced by high accuracy, precision, recall, and F1 score. Moreover, the model's uncertainty estimates correlated with challenging or ambiguous cases, where the model exhibited higher uncertainty. This capability is particularly valuable in clinical decision-making, as it alerts clinicians to cases that may require further expert review or additional tests. The comparison between the uncertainty-aware model and a standard deterministic CNN highlighted the added value of uncertainty estimation in lung ultrasound image analysis. The uncertainty-aware model outperformed the deterministic model in cases where uncertainty was high, emphasizing the importance of incorporating uncertainty estimates in medical decision-making processes. By providing reliable uncertainty estimates, the model can enhance the transparency and interpretability of its predictions, instilling greater confidence in clinicians' diagnostic assessments. However, there are still several avenues for future work in uncertainty-aware lung ultrasound image analysis. Firstly, the dataset used in this study could be further expanded to include a more extensive range of lung pathologies and a larger number of patient samples. This would enable the model to generalize better to diverse patient populations and improve its performance in real-world clinical scenarios. Additionally, investigating different uncertainty quantification methods, such as deep ensemble methods or variational inference techniques, could provide further insights into uncertainty estimation for lung ultrasound image analysis. Comparing various uncertainty quantification approaches may reveal nuances in performance and lead to the development of more robust and accurate uncertainty-aware models. Moreover, exploring the integration of uncertainty estimates into clinical decision support systems could have practical implications. The uncertainty-aware model offers valuable insights into the model's confidence and performance, contributing to more reliable and informed clinical decision-making. As uncertainties are inevitable in medical imaging, this research paves the way for future advancements in uncertainty-aware deep learning models, with the ultimate goal of improving patient care and outcomes in lung disease diagnosis and management.

7. Future directions

The paper concludes with a comprehensive discussion of the findings, highlighting the advantages of deep learning-based uncertainty estimation in lung ultrasound image analysis. Future research directions, including potential applications in real clinical settings and the integration of uncertainty aware models with medical decision support systems, are also explored.

Author contributions

Conceptualization, AGET; methodology, AGET; software, AGET; validation, AGET; formal analysis, AGET; investigation, AGET; resources, JSD; data curation, AGET; writing—original draft preparation, AGET; writing—review and editing, JSD; visualization, AGET; supervision, JSD. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

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