ABSTRACT

Lung cancer is a leading cause of cancer-related deaths, and accurate, early diagnosis is critical for effective treatment. Histopathological analysis is a standard diagnostic approach but requires significant expertise and time. This study aims to improve lung cancer classification through an ensemble of EfficientNetV2 models (B0-B3) applied to histopathological images. EfficientNetV2 was chosen for its scalability and strong performance in image classification tasks. Data augmentation was used to enhance robustness, simulating variability in histopathological slides, while transfer learning from ImageNet pre-trained models enabled faster convergence with limited data. The models were trained on the LC25000 dataset, containing augmented images, and evaluated individually and in ensemble configurations. Grad-CAM provided interpretability, generating heatmaps that highlight model focus, aiding in understanding decision-making. Results showed that individual EfficientNetV2 models achieved near-perfect accuracy, with the ensemble approach further improving performance. Ensemble models, particularly those using hard voting, achieved up to 100% accuracy, precision, and recall, underscoring the effectiveness of combined predictions. However, the high accuracy may be partially due to the dataset's limited unique images, as repeated patterns in augmented data might inflate performance. Future work will test the ensemble on larger, more diverse datasets to validate generalizability. These findings demonstrate the potential of EfficientNetV2 ensembles in lung cancer diagnostics, paving the way for reliable, interpretable AI-based pathology tools in clinical settings.

Keywords: *lung cancer classification, EfficientNetV2, histopathological images, ensemble learning, Grad-CAM*