ABSTRACT

The COVID-19 pandemic has highlighted the need for efficient and reliable diagnostic methods. This thesis explores the integration of artificial intelligence (AI), deep learning, and signal processing techniques to enhance COVID-19 detection through medical imaging and acoustic data analysis.

The research begins with a comprehensive review of the literature, identifying significant advancements and challenges in AI-based COVID-19 detection. Convolutional neural network (CNN) models, utilizing transfer learning with architectures such as VGG16 and ResNet50, are designed to detect COVID-19 from CT scan images. These models are optimized through data augmentation and fine-tuning techniques, showing robust diagnostic capabilities validated by stratified 5-fold cross-validation.

The study also investigates COVID-19 detection using cough sounds, exploring three strategies: machine learning with spectral features, deep learning with ResNet-50, and transfer learning with a Vision Transformer model. The experimental results demonstrate promising performance, suggesting potential applications for non-invasive detection.

A novel Probabilistic Pooling Convolutional Neural Network (PP-CNN) is introduced to enhance image classification. This model integrates probabilistic outputs from MaxPooling, MinPooling, and MaxMinPooling layers, achieving improved accuracy across diverse datasets, including CIFAR-10, CIFAR-100, CT scans, and X-ray images.

Additionally, an innovative approach to analyzing non-stationary signals using generalized constant-overlap-add (COLA) windows and the short-time discrete cosine transform (STDCT) is presented. This methodology enhances time-frequency representation and is applied to detect COVID-19 from cough sounds, validated through experiments on synthetic and real-life data.

This thesis provides significant contributions to AI-based COVID-19 detection, offering robust, non-invasive, and efficient diagnostic methods. The findings pave the way for future research in integrating AI and signal-processing techniques for broader medical applications, ultimately aiming to improve healthcare outcomes.