MULTIPLE DISEASE DETECTION

ABSTRACT

The increasing complexity of healthcare demands innovative solutions for early and accurate disease detection. With advancements in technology, automated diagnostic systems have emerged as a promising alternative to traditional methods, which are often time-consuming, labor-intensive, and prone to human error. Particularly in the case of multiple disease detection, the ability to simultaneously identify and classify various conditions can significantly improve patient outcomes by enabling timely intervention. This research focuses on developing a machine learning-based approach that leverages ensemble techniques to overcome the limitations of existing diagnostic systems and provide a reliable, efficient, and scalable solution for multi-disease detection.

Existing systems primarily rely on individual machine learning models like Support Vector Machines (SVM), Decision Trees, Random Forest, K-Nearest Neighbors (KNN), and Logistic Regression. While these models exhibit satisfactory performance in single-disease detection, their application to multiple diseases is often inadequate due to issues such as overfitting, lack of generalization, and sensitivity to imbalanced datasets. Furthermore, these models struggle to handle complex, high-dimensional medical data, leading to reduced accuracy and increased misclassification rates. Despite the potential of ensemble learning approaches, they remain underutilized in the context of multiple disease detection, leaving room for innovation and improvement.

The proposed system addresses these challenges by introducing an ensemble learning model that combines SVM, Decision Trees, Random Forest, KNN, and Logistic Regression into a unified framework. This approach leverages the strengths of each individual algorithm, enabling the model to reduce bias, variance, and noise while improving overall predictive accuracy. By integrating these diverse models, the system achieves superior performance in detecting multiple diseases simultaneously. Experimental results on benchmark datasets demonstrate that the ensemble model outperforms standalone models, achieving an average accuracy of 95%, compared to 88% for Logistic Regression, 89% for SVM, 91% for Random Forest, and 90% for KNN. The proposed system also offers enhanced adaptability to imbalanced datasets and ensures scalability across various medical applications.

In conclusion, this research highlights the transformative potential of ensemble learning in addressing the limitations of existing diagnostic models for multi-disease detection. By combining the predictive power of multiple algorithms, the proposed system not only improves accuracy but also establishes a robust and efficient framework for medical diagnostics. This innovation paves the way for more effective and timely healthcare delivery, offering a significant leap forward in automated disease detection.

Keywords: Multi-disease detection, ensemble learning, machine learning, SVM, Decision Trees, Random Forest, KNN, Logistic Regression.

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