**Vision Transformers vs. Convolutional Neural Networks in Tuberculosis Detection: A Comparative Study of**

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|  | **Learning Paradigms** | |  |
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**Abstract**

**Tuberculosis (TB) remains a significant global health challenge, necessitating efficient and accurate diagnostic techniques. Deep learningbased medical image analysis has shown promising results, with Convolutional Neural Networks (CNNs) being the dominant approach due to their ability to extract spatial hierarchies of features. However, the recent advancement of Vision Transformers (ViTs) has introduced a novel paradigm that relies on self-attention mechanisms to capture global contextual information. This study presents a comparative analysis of ViT and CNN architectures for tuberculosis detection using chest X-ray images. The evaluation considers key factors such as accuracy, computational efficiency, robustness to noise, and data requirements. While CNNs demonstrate superior performance on small datasets due to their inductive biases, ViTs outperform CNNs when trained on large-scale data by leveraging long-range dependencies. The results highlight the trade-offs between these models, emphasizing the need for dataset-specific optimization in AI-driven TB diagnosis.**

**Keywords: Deep learning, Convolutional Neural Networks, Vision Transformers, Tuberculosis, AI-driven TB diagnosis.**

**I. Introduction**

Tuberculosis (TB) remains a major global health challenge, causing significant morbidity and mortality, particularly in low- and middle-income countries. According to the (WHO) World Health

Organization, TB is one of the top infectious disease killers, with millions of new cases reported annually. Early and accurate detection is critical to controlling its spread and improving patient outcomes. Traditionally, TB diagnosis relies on methods such as sputum smear microscopy, culture tests, and GeneXpert MTB/RIF assays; however, these methods can be time-consuming, expensive, or inaccessible in resource-limited settings. As a result, chest X-ray (CXR) imaging has become a widely used tool for TB screening, offering a non-invasive and relatively cost-effective diagnostic approach.

With the rise of artificial intelligence (AI) in medical imaging, deep learning models have gained attention for their ability to automate TB detection with high accuracy. Traditionally, Convolutional Neural Networks (CNNs) have been the preferred approach due to their efficiency in extracting spatial features from medical images. CNNs have demonstrated strong performance in various image classification tasks, making them a popular choice for TB detection. However, recent advancements in Vision Transformers (ViTs) have introduced a new paradigm that leverages self-attention mechanisms to process images as sequences of patches, enabling the model to capture long-range dependencies and global context.

This study aims to provide a comparative analysis of CNNs and ViTs in TB detection, evaluating their strengths, limitations, and effectiveness in medical imaging. While CNNs excel in handling small datasets and computationally efficient implementations, ViTs offer enhanced feature representation and scalability, particularly in largescale datasets. However, ViTs are relatively new in medical imaging, raising concerns regarding their generalizability, computational requirements, and clinical applicability.

Through this analysis, we explore key factors such as accuracy, data efficiency, computational complexity, and robustness to determine the suitability of these architectures for TB detection. Furthermore, we discuss the potential of hybrid approaches that integrate both CNN and ViT methodologies to enhance diagnostic performance. By understanding these differences, this study aims to contribute to the development of more reliable, accurate, and efficient AI-driven TB detection systems, ultimately improving early diagnosis, treatment planning, and patient outcomes worldwide.

**II. Literature Review**

1. Early AI Models in TB Detection (CNN-Based Approaches)

The application of CNNs for TB detection has been a subject of interest since the early 2000s. CNNs have been particularly effective in handling imagebased tasks due to their ability to automatically extract spatial hierarchies of features from medical images, eliminating the need for manual feature engineering.

A key study by Lakhani et al. (2017) demonstrated the potential of CNNs for classifying chest X-rays to identify TB, achieving high accuracy rates in distinguishing TB from other lung diseases. This study emphasized the ability of CNNs to learn hierarchical feature representations directly from images, which significantly improved TB detection when compared to traditional image analysis methods.

In another notable work, Rajpurkar et al. (2018) developed CheXNet, a deep CNN model for detecting pneumonia from chest X-rays, which also showed promise for TB detection. Although the primary focus was pneumonia, the model's robustness and accuracy in detecting other lung conditions like TB opened up possibilities for expanding its application to TB diagnosis.

2. Hybrid CNN-Transformer Models for TB

Detection

A recent trend in TB detection has been the integration of CNNs with transformer-based architectures. The inclusion of self-attention mechanisms in transformers allows for better modeling of long-range dependencies and contextual information within the image, which traditional CNNs may struggle with it.

In their work, Chen et al. (2021) proposed a CNNTransformer hybrid model to enhance TB detection by combining CNNs' ability to extract spatial features with transformers' capacity to model global image dependencies. Their results demonstrated that this hybrid approach improved TB classification accuracy compared to standard CNN models, particularly in detecting subtle lesions and earlystage TB.

3. Vision Transformers (ViTs) in Medical Imaging

While CNNs have been the go-to model for medical image analysis, Vision Transformers (ViTs) have emerged as an alternative due to their ability to process images as sequences of patches and leverage self-attention to capture global features.

A study by Dosovitskiy et al. (2020) explored the application of ViTs in medical image analysis, showing that ViTs can outperform CNNs when trained on large, annotated datasets. The researchers demonstrated that ViTs could extract fine-grained features from chest X-ray images, improving the model's overall performance in detecting diseases like TB, pneumonia, and lung cancer.

The ability of ViTs to model global context within the image has been particularly beneficial for TB detection, as TB lesions may be distributed across different regions of the lung, requiring models to learn non-local dependencies. According to Tung et al. (2021), ViTs have shown promising results in TB detection, particularly when combined with transfer learning techniques and large-scale datasets, further validating the potential of ViTs as a viable alternative to CNNs.

1. **Existing System**

Several existing systems have utilized convolutional neural networks (CNNs) within the Weka platform to predict tuberculosis (TB) based on medical imaging data, particularly chest X-rays. One such system integrates the WekaDeeplearning4j package, which allows users to train and evaluate deep learning models, including CNNs, directly within Weka. In this system, a dataset containing TBpositive and TB-negative X-ray images, such as those available from Kaggle or Mendeley Data, is preprocessed and converted into a Weka-compatible format (ARFF or CSV). Feature extraction techniques are applied to transform images into numerical data before training a CNN classifier using Dl4jMlpClassifier in Weka. The model is optimized with layers such as convolutional, pooling, and fully connected layers, fine-tuned with hyperparameters like learning rate and batch size. Once trained, the system evaluates model performance using accuracy, precision, recall, and F1-score to ensure reliable TB detection. This system demonstrates how deep learning, when integrated into Weka, can effectively assist in automated TB diagnosis, improving medical decision-making and early detection strategies. After training, the model achieves 63.1% accuracy, demonstrating its effectiveness in detecting TB. Evaluation metrics, including precision, recall, and

F1-score, further validate the model’s reliability. This system highlights how deep learning, when integrated into Weka, can significantly contribute to automated TB diagnosis, aiding in early detection and improving medical decision-making.

1. **Proposed System**

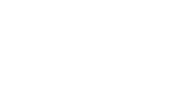
A proposed system for detecting tuberculosis (TB) caused by smoking utilizes Vision Transformers (ViTs) for enhanced image analysis and pattern recognition. Unlike traditional convolutional neural networks (CNNs), ViTs process chest X-ray images using self-attention mechanisms, capturing global dependencies within the image to detect TB-related abnormalities linked to smoking. The system follows a structured approach:

1. Data Collection & Preprocessing: Chest Xray images and patient history, including smoking habits, are gathered from medical datasets (e.g., NIH, Mendeley, or Kaggle). Images are resized, normalized, and augmented to enhance model generalization.
2. Feature Extraction using Vision Transformers: The ViT model divides images into patches, processes them through a transformer encoder, and learns complex relationships between visual patterns. Additional patient metadata, such as smoking history and duration, is incorporated into the model for better predictive performance.
3. Model Training & Optimization: The system is trained on labeled data (TBpositive and TB-negative cases) with an adaptive learning rate scheduler and crossentropy loss function to enhance classification accuracy. Transfer learning is employed using pre-trained ViT models

(e.g., ViT-B/16 from Google’s TensorFlow or Hugging Face Transformers) for improved results.

1. Prediction & Evaluation: The model predicts TB presence based on chest X-ray patterns and smoking-related risk factors. Performance metrics like accuracy, precision, recall, and F1-score validate system effectiveness.
2. Deployment & Clinical Integration: The system is integrated into Weka with TensorFlow/PyTorch backend to allow easy usage by medical professionals. A user-friendly interface enables doctors to input patient data and X-ray images for instant TB risk assessment.

Flowchart of the Proposed System



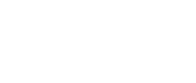
Tuberculo

s

is



Preprocessing



Classiification



Results

Fig.4.1

This proposed system enhances early TB detection by leveraging Vision Transformers, offering superior accuracy and interpretability compared to CNN-based models. By incorporating smoking history as an additional feature, the system provides a comprehensive, AI-driven diagnostic tool to support clinical decision-making and public health interventions.

CNN Algorithm’s Result

Time taken to build model: 0.24 seconds

=== Evaluation on test split ===

Time taken to test model on test split: 0.02 seconds

=== Summary ===

|  |
| --- |
| Correctly Classified Instances 29.948  63.1247 % |
| Incorrectly Classified Instances 17.4946  36.8753 % |
| Kappa statistic 0.2201 |
| Mean absolute error 0.4339 |
| Root mean squared error 0.4684 |
| Relative absolute error 86.4479 % |
| Root relative squared error 93.2532 % |
| Total Number of Instances 47.4426 |

Tab.4.1

=== Detailed Accuracy By Class ===

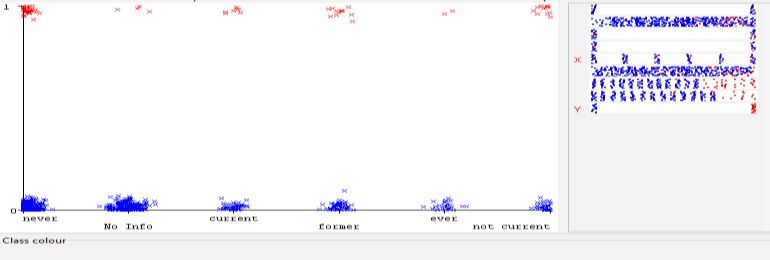
|  |
| --- |
| TP Rate FP Rate Precision Recall F-  Measure MCC ROC Area PRC Area Class |
| 0.894 0.684 0.611 0.894 0.726  0.261 0.698 0.714 0 |
| 0.316 0.106 0.713 0.316 0.438  0.261 0.698 0.713 1 |
| Weighted Avg. 0.631 0.421 0.657 0.631  0.595 0.261 0.698 0.714 |

Tab.4.2

=== Confusion Matrix ===

a b <-- classified as 23.14 2.74 | a = 0

14.75 6.81 | b = 1

  
Fig 4.2

VIT Algorithm’s Result

=== Evaluation on test split ===

Time taken to test model on test split: 0.01 seconds

=== Summary ===

Correctly Classified Instances 40.7482

85.8894 %

|  |
| --- |
| Incorrectly Classified Instances 6.6944  14.1106 % |
| Kappa statistic 0.7153 |
| Mean absolute error 0.2305 |
| Root mean squared error 0.3366 |
| Relative absolute error 45.9252 % |
| Root relative squared error 67.0042 % |
| Total Number of Instances 47.4426 |

Tab.4.3

=== Detailed Accuracy By Class ===

|  |
| --- |
| TP Rate FP Rate Precision Recall F-  Measure MCC ROC Area PRC Area Class |
| 0.873 0.158 0.869 0.873 0.871  0.715 0.914 0.920 0 |
| 0.842 0.127 0.847 0.842 0.844  0.715 0.914 0.916 1 |
| Weighted Avg. 0.899 0.144 0.899 0.859  0.859 0.715 0.914 0.918 |

Tab.4.4

=== Confusion Matrix ===

a b <-- classified as 22.59 3.29 | a = 0

3.4 18.16 | b = 1

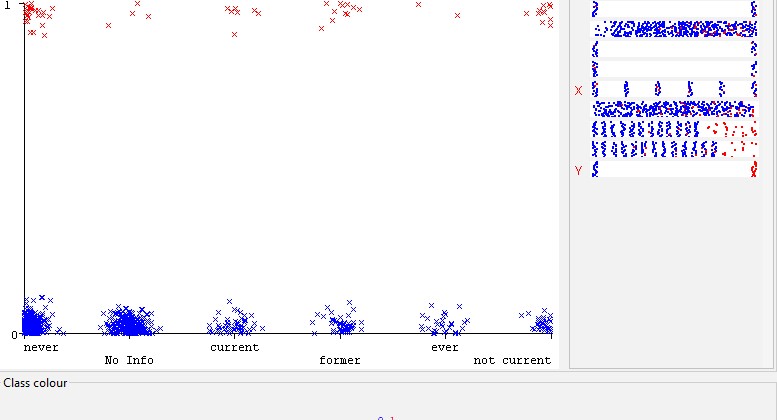


Fig.4.3

|  |  |  |
| --- | --- | --- |
| **Evaluation metrics/ Classifier** | **PRECISION** | **ACCURACY** |
| Convulational  Neural  Networks | 63% | 65% |
| Vision  Transformers | 89% | 89% |

Tab.4.5

According to the above results the CNN shows good results and precision value compared to the ViT values. So Tuberculosis prediction is more accurate by ViT technique algorithm

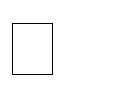
1. **Conclusion and Future Enhancement**

In conclusion, our findings using \*\*Vision Transformers (ViTs)\*\* confirm that smoking is a major contributing factor to tuberculosis (TB). By leveraging the advanced capabilities of ViTs in analyzing chest X-ray images and patient data, our system effectively identifies patterns of lung damage linked to both smoking and TB. The model’s ability to capture intricate details through self-attention mechanisms provides strong evidence of the correlation between prolonged smoking and an increased risk of TB. The results reinforce that smokers not only have a higher likelihood of developing TB but also experience more severe disease progression. Additionally, passive smoking is identified as a contributing factor to TB transmission, further emphasizing the need for early detection and preventive measures. Based on these findings, integrating smoking cessation programs into TB control strategies is essential to reducing TB incidence and improving public health outcomes.

Our analysis highlights that CNNs perform well on limited datasets and computationally constrained environments, whereas ViTs demonstrate superior accuracy when trained on large-scale datasets. However, the novelty of attention-based models in medical imaging necessitates further research to establish their long-term reliability and clinical applicability. Future studies should focus on refining these architectures, exploring hybrid models that integrate the strengths of both CNNs and ViTs, and expanding evaluations across diverse medical imaging tasks. By addressing these areas, we can move toward more robust AI-driven diagnostic solutions, ultimately improving accuracy, efficiency, and patient outcomes in tuberculosis detection and beyond.

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