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AUTOMATED DETECTION OF TUBERCULOSIS FROM CHEST X-RAY IMAGES USING DEEP LEARNING

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ABSTRACT:
One of the most common and deadly infectious illnesses in the world is still tuberculosis (TB), especially in developing nations with inadequate healthcare systems. In order to stop the spread of tuberculosis and enhance patient outcomes, early identification and diagnosis are essential. In this study, we present a deep learning-based system that uses chest X-ray pictures to automatically detect tuberculosis. Despite the difficulties of limited dataset availability, the system uses transfer learning using MobileNetV2 and DenseNet architectures to classify chest X-rays as either TB-positive or Healthy, reaching notable accuracy. To increase model generalisation and image quality, pre-processing methods like Contrast Limited Adaptive Histogram Equalisation (CLAHE) and sophisticated data augmentation approaches are used. The trained model is then implemented as a Flask web application, offering a user-friendly interface with features like secure login, image upload and preview, prediction results with probability scores, and performance metrics visualisation like accuracy curves, confusion matrices, and ROC curves. The suggested framework shows how deep learning can be used to create scalable, dependable, and affordable diagnostic tools to help radiologists and other medical professionals with TB screening and diagnosis.

1. INTRODUCTION:

One of the most serious infectious illnesses in the world, tuberculosis (TB) mostly affects the lungs and kills millions of people annually, especially in low- and middle-income nations. Controlling the spread of tuberculosis and enhancing treatment results depend heavily on early and precise detection. Sputum microscopy and culture tests are examples of traditional diagnostic techniques that are time-consuming, expensive, and frequently unavailable in environments with limited resources. Due to its affordability and ease of use, medical imaging, especially chest X-rays, has gained popularity as a TB screening method in recent years. However, radiologists' manual interpretation of X-rays is subjective and prone to mistakes, particularly when there are mild or overlapping symptoms. Deep learning-based methods have demonstrated impressive progress in automating medical image processing thanks to developments in artificial intelligence. Convolutional neural networks (CNNs) and transfer learning models such as ResNet, MobileNetV2, and DenseNet have shown promise in identifying intricate patterns in chest X-rays and accurately classifying images into TB-positive and healthy categories. In order to enable quicker and more accurate TB diagnosis, this project focuses on creating a deep learning-based TB detection system employing chest X-ray pictures, supplemented using preprocessing and augmentation techniques, and deployed as an intuitive Flask web application.

1.1 OBJECTIVE:

This project's main goal is to create an intelligent, precise, and user-friendly system for detecting tuberculosis from chest X-ray pictures. In order to minimise diagnostic errors and lessen reliance on manual interpretation, the project will use cutting-edge deep learning algorithms, specifically MobileNetV2 and DenseNet121, to automatically identify chest X-rays as TB-positive or healthy. Enhancing the model's performance through preprocessing techniques like CLAHE and efficient data augmentation is another crucial goal, guaranteeing that the system performs effectively even on tiny and unbalanced datasets. A user-friendly Flask-based online application that enables users to safely log in, upload X-ray photos, preview them, and instantaneously receive prediction results along with confidence scores is another goal of the project. The incorporation of model performance visualisations, such as ROC analysis, confusion matrices, and training curves, enhances the system's dependability and transparency. The ultimate goal is to offer a scalable and affordable technology that can help medical professionals diagnose tuberculosis early, enhance patient outcomes, and support international TB control initiatives.

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2. EXISTING SYSTEM:

The current tuberculosis (TB) detection method uses transfer learning models in conjunction with deep learning. ResNet50, a convolutional neural network (CNN) initially intended for large-scale image classification applications, is one of the most popular models. ResNet50 improves the accuracy of training very deep networks by using residual connections to solve vanishing gradient issues.

2.1 Existing System Disadvantages:

- Limited Dataset Diversity
- Image Quality Assumptions
- Potential Labeling Errors
- Binary Classification Limitation
- Lack of Additional Clinical Data

3. LITERATURE SURVEY:

WHO's Global Tuberculosis Report 2022-2023, S. Bagcchi.

This report provides a comprehensive analysis of the global tuberculosis situation, highlighting the prevalence, mortality rates, and challenges in TB detection and treatment. It emphasizes the urgent need for innovative diagnostic approaches and improved healthcare infrastructure to tackle the disease burden effectively. The insights from this report underline the importance of integrating automated deep learning systems to support early TB detection and reduce the gap in clinical diagnosis.

Optimizing Chest Tuberculosis Image Classification with Oversampling and Transfer Learning, 2024, A. Alqahtani, Q. A. Al-Haija, A. A. Alsulami, B. Alturki, N. Alqahtani, and R. Alsini

This research explores the use of oversampling techniques combined with transfer learning models to address the class imbalance issue in TB datasets. The study demonstrates that transfer learning with optimized preprocessing significantly enhances the accuracy of TB classification from chest X-rays. This work is highly relevant to the proposed project as it validates the use of modern deep learning architectures in overcoming dataset limitations.

4. RELATED WORK:

Deep learning methods for detecting tuberculosis from chest X-ray pictures have been investigated in a number of research. To solve class imbalance in TB datasets, Alqahtani et al. suggested a transfer learning-based strategy in conjunction with oversampling techniques. Their research showed that transfer learning and picture preprocessing greatly enhance detection accuracy and classification performance.

In order to diagnose tuberculosis from chest radiographs, Saif et al. developed a cascaded ensemble feature extraction framework that combines several feature representations. By combining both hand-crafted and deep learning features, their method increased classification accuracy and robustness. In a similar vein, Roopa and Mamatha created a CNN-based model especially for TB detection, demonstrating the usefulness of convolutional neural networks in medical picture processing and producing accurate prediction results.

In order to reliably detect tuberculosis from chest X-rays, Rahman et al. introduced a deep learning architecture that incorporates image segmentation and visualisation approaches. Their research highlighted the significance of explainability and preprocessing in enhancing diagnostic performance. Additionally, recent research has demonstrated that transfer learning models like ResNet, DenseNet, and MobileNetV2 may achieve excellent accuracy with little medical datasets, which makes them appropriate for real-world healthcare applications and automated TB screening systems.

5. PROPOSED SYSTEM:

The suggested system automatically detects tuberculosis from chest X-ray pictures using deep learning-based transfer learning techniques. Transfer learning enables the extraction of significant characteristics from medical pictures using pretrained convolutional neural network (CNN) architectures that have been trained on extensive datasets like ImageNet. This method maintains good accuracy while drastically reducing the demand for big labelled medical datasets. To categorise chest X-rays into TB Positive and Healthy categories, the pretrained models are refined using the tuberculosis dataset.

5.1 Proposed System Advantages:

- High Accuracy with Small Data
- Lightweight & Fast
- Robust Feature Extraction
- Scalability

6. MODULES:

Data Collection and Pre-processing Module:

The collection of chest X-ray datasets, such as Sakha-TB and TBX11K, is the main goal of this module. By resizing, normalising, and using pre-processing methods like CLAHE and histogram equalisation to improve contrast, the photos are standardised. To increase the diversity of the dataset and decrease overfitting, data augmentation techniques including flipping, rotation, brightness adjustment, and zooming are used. This ensures that the model performs well when applied to previously unknown photos.

Dataset Splitting Module:

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Training, validation, and testing sets are created from the gathered dataset. The test set is set aside for final evaluation, the validation set aids in hyperparameter tuning and overfitting monitoring, and the training set is utilised to train the MobileNetV2B3 model. To prevent bias in classification outcomes, this module makes sure that the distribution of classes is balanced across splits.

Model Development Module:
The MobileNetV2B3 transfer learning model is implemented in this module. The final layers are adjusted for binary classification (healthy vs. tuberculosis) using pre-trained ImageNet weights as the foundation. The Adam optimiser, accuracy as the evaluation metric, and categorical/binary cross-entropy loss are used to assemble the model. To enhance model performance and stability, sophisticated regularisation strategies including dropout and learning rate scheduling are also used.

Training and Validation Module:
Batch-based learning is used to train the MobileNetV2B3 model on the prepared dataset. Callbacks like Early Stopping and Reduce LROn Plateau are used during training to dynamically modify the learning rate to avoid overfitting. The best-performing model is saved for deployment after training and validation accuracy/loss are continuously tracked.

Model Evaluation and Visualization Module:
This module uses the test dataset to assess the trained model. Performance measures are calculated, including recall, accuracy, precision, F1-score, and confusion matrix. To further shed light on model performance and potential areas for development, visualisation tools including as ROC curves, confusion matrices, and training/validation accuracy and loss curves are created.

Prediction and Image Processing Module:
Real-time prediction is handled by this module. Uploaded chest X-ray pictures are supplied into the trained model after being pre-processed. The result is a prediction with a confidence score that shows if the patient is healthy or infected with tuberculosis. For easier results interpretation, both the original and pre-processed photos are shown.

Web Application Integration Module:
This module incorporates a Flask-based web application with the trained model. A home site, temporary registration and login, image upload and preview, prediction results with image display, and a charts page displaying evaluation metrics comprise its user interface. This guarantees that the system is practical, easy to use, and accessible for implementation in healthcare environments.

7. TECHNIQUE USED:

7.1 EXISTING TECHNIQUE:

- **ResNet50**

A deep learning architecture called ResNet50, or Residual Network with 50 Layers, was created to overcome the difficulties associated with training extremely deep neural networks. Instead of learning the complete transformation directly, it incorporates residual connections, which enable the network to learn residual functions (differences between input and output). In order to accomplish this, shortcut connections that avoid one or more layers are added, allowing the model to merge a layer's input and output. The vanishing gradient problem, which causes deeper networks to have difficulty learning because of diminishing gradients during back propagation, is lessened by this method. ResNet50 is composed of numerous residual blocks with different filter sizes (e.g., 64, 128, 256, 512, and 1024 filters), max-pooling, and a 7x7 convolutional layer with 64 filters. In the context of Crack Vision, ResNet50 is refined to identify patterns unique to cracks in concrete photos after being pre-trained on the ImageNet dataset to identify broad image features like edges and textures Even with unbalanced datasets, the model's ability to classify concrete surfaces as cracked or non-cracked is much improved by this transfer learning technique, which also shortens training times and improves generalisation.

7.2 PROPOSED TECHNIQUE USED:

- **MobileNetV2**

MobileNetV2 is a lightweight and efficient convolutional neural network (CNN) architecture developed by Google for image classification and computer vision tasks. It is designed to deliver high accuracy while requiring fewer computational resources, making it suitable for mobile devices and embedded systems. MobileNetV2 introduces two key innovations: depth wise separable convolutions, which reduce the number of computations, and inverted residual blocks with linear bottlenecks, which improve feature extraction while keeping the model compact. In deep learning applications, MobileNetV2 is widely used for transfer learning, where a pre-trained model is fine-tuned on a specific dataset. In medical image analysis, such as tuberculosis detection from chest X-rays, MobileNetV2 effectively extracts important visual features, resulting in faster training, lower memory usage, and reliable classification performance.

8. RESULTS:

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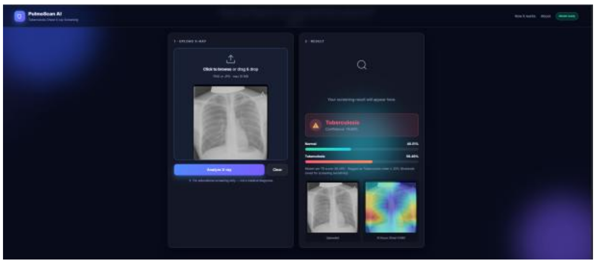

9. CONCLUSION:

This experiment shows how well sophisticated deep learning methods—more especially, MobileNetV2B3 transfer learning—can be used to identify tuberculosis from chest X-ray pictures. The system attains excellent accuracy and dependable classification performance by utilising preprocessing, data augmentation, and fine-tuning techniques. Healthcare professionals will find the solution useful, easy to use, and accessible thanks to the integration of the trained model into a Flask-based web application. In addition to outperforming the base paper's conventional CNN-based techniques, this work emphasises the potential of AI-driven diagnostic systems in promoting early tuberculosis identification, lowering manual diagnostic errors, and assisting with prompt treatment decisions. In the end, this initiative advances the development of scalable, automated, and affordable medical diagnostic instruments that can be vital to the management of tuberculosis worldwide and the advancement of public health.

10. FUTURE ENHANCEMENTS:

The proposed Tuberculosis Detection System can be further enhanced by training the model on larger and more diverse chest X-ray datasets to improve accuracy and generalization. Future versions can be extended to detect multiple lung diseases, such as pneumonia, COVID-19, and lung cancer, making the system more versatile. Deploying the application on cloud platforms and mobile devices would improve accessibility and support remote diagnosis. Integration with hospital information systems (HIS/PACS) would enable seamless adoption in clinical environments, while continuous model retraining using new medical data would help maintain high performance, accuracy, and reliability over time.

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