**Proposed Topic:** Bone Tuberculosis Detection Using Machine Learning

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**Objective**

The objective of this project is to develop a machine learning model capable of detecting bone tuberculosis (TB) from medical imaging data, specifically X-ray and MRI scans. This model aims to assist in early diagnosis, thus facilitating timely intervention and improving patient outcomes. By identifying unique patterns associated with bone TB, the model will provide a reliable tool for medical practitioners. Ultimately, the model will be integrated into a software solution accessible to healthcare providers.

**Motivation**

The motivation for developing a model for bone tuberculosis detection is that in countries like Niger Republic, and in West Africa, TB poses a significant health burden due to limited healthcare infrastructure, high rates of HIV co-infection, and late diagnosis. Niger, along with other countries in this region, experiences high TB incidence rates. In 2021, for instance, West Africa reported over 325,000 TB cases with an annual mortality rate from TB that exceeds available healthcare capacities. This burden is enhanced by Niger’s 44% poverty rate, where healthcare access is limited, and patients face high out-of-pocket medical expenses.

In Niger and other West African nations, the scarcity of specialized diagnostic tools, such as advanced imaging and molecular diagnostics, means that TB, especially extrapulmonary cases like bone TB, often goes undiagnosed or is detected too late for effective treatment. Thus, the introduction of a detection system would not only enhance diagnostic accuracy but also reduce reliance on specialist radiologists, which are scarce in Niger, making TB diagnosis more accessible and timely.

**Prior Work**

Significant strides have been made in using machine learning (ML) for tuberculosis (TB) detection, primarily within pulmonary contexts. For instance, Lakhani and Sundaram employed convolutional neural networks (CNNs) on chest radiographs, achieving an accuracy rate over 90% for pulmonary TB detection [1].

Similarly, researchers from the Radiological Society of North America utilized CNN-based systems to detect TB in chest X-rays, demonstrating diagnostic accuracy comparable to radiologists' evaluations [2].

Despite these advances, the application of ML for extrapulmonary TB, including bone TB, remains limited, with MRI and CT imaging—typically used for bone—being less accessible in regions with limited healthcare infrastructure.

Molecular approaches, such as GeneXpert MTB/RIF, have also improved TB diagnosis by detecting bacterial DNA with high sensitivity. However, the cost and infrastructure requirements of GeneXpert present barriers in low-resource settings like Niger [3].

Although rapid diagnostic tests (RDTs) and nucleic acid amplification tests (NAATs) are promising for quick detection, their application to bone tissue remains challenging [4].

Histopathology remains a gold standard for diagnosing extrapulmonary TB, yet it requires highly trained personnel and sophisticated equipment. Gupta et al. investigated the potential for digital pathology combined with deep learning models to identify TB bacilli in histopathology slides, showing promise for automated diagnostics [5]. However, these methods require high-resolution images and computational resources, which are often unavailable in rural West African settings.

**Proposed Improvements**

The limitations of current approaches highlight the need for a low-cost, accessible model tailored specifically to bone TB. This project seeks to extend CNN-based advancements by developing a model trained on bone-specific imaging data, possibly utilizing transfer learning to adapt existing pulmonary TB models to extrapulmonary presentations. By focusing on a resource-efficient ML model that can operate on limited imaging data, this approach aims to enhance diagnostic specificity and accessibility in low-resource environments.

### Methods

1. **Data Collection and Preprocessing**: I will start by acquiring a labeled dataset of bone TB images, specifically focusing on X-ray and MRI scans to capture TB-related markers in bone structures. This data will come from open-access databases and local hospital visits, where I aim to collect relevant cases directly from radiology departments. The preprocessing stage will include normalizing the scales of the images and enhancing features that are indicative of bone TB, such as lesions or abnormal bone densities. This step will ensure that the images are optimized for accurate model training.
2. **Model Selection**: For model architecture, I will experiment with several options to identify the one best suited for detecting TB-specific features in bone. I’ll test popular deep learning models like CNNs and pretrained architectures such as ResNet and VGG, as these models have shown strong performance in medical imaging tasks. After selecting the most promising architecture, I’ll fine-tune the model on the bone TB dataset to ensure it can accurately learn and recognize the specific patterns associated with the disease.
3. **Training and Evaluation**: The model will be trained on the labeled dataset and validated on a separate test set. To ensure that the model meets clinical standards, I’ll evaluate its performance using metrics like sensitivity, specificity, and F1-score. These metrics will allow me to assess the model's diagnostic accuracy and relevance for real-world applications in TB detection.
4. **Deployment and Testing**: Once the model is validated, I’ll deploy it within a prototype software application. This application will enable users to upload bone images and receive diagnostic feedback from the model. This interface will display the detection results clearly, allowing medical practitioners to interpret the outputs effectively and facilitating quicker diagnosis and treatment of bone TB.

This methodology is designed to ensure the final system is not only accurate but also practical for use in clinical and resource-limited settings.

**Deliverables**:

1. **Trained Machine Learning Model for Bone TB Detection**: The core deliverable will be a high-performing, trained machine learning model capable of detecting bone tuberculosis with accuracy and reliability. This model will be fine-tuned for detecting the subtle indicators of TB in bone structure using radiological data, primarily X-rays and MRI scans. Rigorous testing and validation will ensure that it meets clinical standards, with the model performing well across various metrics, such as sensitivity and specificity, for consistent diagnostic support.
2. **Prototype Software Application with Image Upload and TB Detection Interface**: To make the model accessible and functional in practical settings, I’ll integrate it into a prototype software application. This application will feature a user-friendly interface, allowing healthcare providers or technicians to upload patient images and receive immediate, diagnostic feedback. The output will include TB detection results displayed in a clear and concise format, helping guide medical decision-making in both clinical and resource-limited environments.
3. **Comprehensive Final Report**: The project will culminate in a final report, which will detail each aspect of the methodology, results, and findings. It will include an overview of the data collection and preprocessing phases, model architecture selection, performance metrics, and the development of the prototype application. The report will also outline potential avenues for future work, such as expanding the model’s application to other forms of extrapulmonary TB or adapting the software for mobile platforms, thus broadening its utility in rural or under-resourced healthcare settings.

**Resources**

This project requires:

* Access to a GPU-enabled computer for training deep learning models.
* A dataset of X-ray and MRI images specific to bone TB.
* Software frameworks and libraries for machine learning (e.g., TensorFlow or PyTorch) and image processing (e.g., OpenCV).
* Ethics approval to access and use medical imaging data if sourced directly from healthcare facilities.

Currently, I have access to GPU enabled computer and the software libraries and frameworks. Access to the dataset will be made available under my supervisor’s guidance especially as it relates to images from the medical centers.

**References**

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**Milestones**

* Data Acquisition and Ethics Approval: Complete by November, Week 2.
* Data Preprocessing and Initial Model Training: Complete by December, Week 1.
* Model Evaluation and Optimization: Complete by January, Week 2.
* Prototype Software Development: Complete by February, Week 1.
* Final Report and Presentation Preparation: Complete by February, Week 4.