Deep learning techniques for the detection of Mesothelioma Cancer

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Abstract:

Mesothelioma, a rare and aggressive cancer primarily caused by prolonged exposure to asbestos, presents significant challenges in early detection and accurate diagnosis. Traditional diagnostic methods often rely on imaging and histopathological analysis, which are subject to inter-observer variability and delayed interpretation. Recent advancements in artificial intelligence, particularly deep learning (DL), have demonstrated significant potential in enhancing diagnostic accuracy and reducing diagnostic latency in various medical domains. This research paper presents an in-depth exploration of deep learning techniques for the detection of Mesothelioma cancer, covering the use of various architectures such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and hybrid models. The study integrates imaging data, histopathological slides, and clinical records to build robust and interpretable models. We discuss model performance, interpretability, challenges in data collection, and propose future directions, including federated learning and explainable AI to facilitate clinical adoption.

Keywords: Deep learning; mesothelioma detection; CNN; RNN; classification;

Introduction

Mesothelioma is a malignancy that affects the mesothelium, a protective lining covering the lungs, abdomen, heart, and testicles. The most common type is pleural mesothelioma, which affects the lung lining. It is strongly associated with occupational and environmental asbestos exposure. The latency period of Mesothelioma ranges from 20 to 50 years, making early diagnosis challenging. Due to its nonspecific symptoms—such as chest pain, breathlessness, and weight loss—many cases are diagnosed at a late stage, reducing survival rates [1] [2].

Despite advances in imaging technologies and pathological diagnostics, the complexity of Mesothelioma requires more accurate, faster, and automated diagnostic methods. Deep learning, a subset of machine learning, has gained momentum in medical imaging and disease prediction. It can automatically extract features from large datasets without manual intervention, enabling real-time, high-accuracy diagnosis. This research investigates how deep learning techniques can enhance Mesothelioma detection through comprehensive experimental analysis [3] [4].

Numerous studies have demonstrated the effectiveness of DL models in cancer diagnostics, notably for breast cancer, lung cancer, and melanoma. CNNs, with their layered architecture designed for spatial data, have revolutionized image-based classification. RNNs, capable of handling sequential data, are often used in processing clinical records and patient histories. Hybrid models combining CNN and RNN have shown improved outcomes in scenarios requiring both spatial and temporal analysis [5].

In contrast, Mesothelioma has received limited attention in the DL research landscape. A few notable studies have attempted binary classification using small datasets with traditional machine learning models like Support Vector Machines (SVM) and k-Nearest Neighbors (k-NN). These methods, while effective for small datasets, do not scale well or provide the nuanced decision-making required in clinical settings. Therefore, our study addresses this research gap by proposing a comprehensive DL-based diagnostic pipeline[6].

Related work

Papik et al. [7] conducted a literature review covering the previous five to six years in order to provide a concise introduction to the topic. The review focused on the papers that are most relevant to the debate and provided examples of how neural networks may be used in medicine. The review was conducted in order to provide a concise introduction to the topic. They looked at a few different medical situations in order to have a better understanding of the problem of research into the applications of neural networks. It is essential to emphasise the fact that the use of this innovative technology will hasten the production of diagnostic tools that are at the forefront of their fields in terms of gastrography, electrocardiography, and microscopy.

In his paper [8], Muhammad Imran Razzak investigated current advancements in the architecture of deep learning and its optimization for the segmentation and classification of medical images. This article presents a comparison of a wide variety of different deep learning model architectures. They discussed some of the challenges that are encountered when using deep learning to medical imaging. They discovered that deep learning has its own special challenges, such as a lack of data, privacy and legal problems, the need for highly skilled medical workers, atypical data and ML methodologies, and a great deal more besides. Deep learning, on the other hand, has shown to be an effective strategy for overcoming challenges of this kind. The so-called "black-box issue" occurs when the building of a neural network is straightforward but it is impossible to specify how the needed output was achieved. The deep learning technique is also notable for its level of complexity and has gained widespread acceptance within the academic world while receiving little to no criticism. Since anyone is able to make a contribution to this area of research, a large number of institutions, including some of the most prestigious educational establishments, healthcare facilities, and information technology businesses in the world, are working together to locate the most effective solution for medical imaging on a global scale.

In order to pinpoint the location of the tumour in MR scans, Muhammad and Yun [9] investigated and used five distinct image segmentation techniques. Among these approaches were the Watershed Segmentation Method, the Fuzzy C-Mean Method, the Seeded Region Growing Method, and the Histogram Threshold Method. The evaluations of the two procedures, both statistically and aesthetically, reveal that the method of constructing seeded regions is better to other analytic processes. After taking into account the peculiarities of medical photographs and the pressing need to differentiate between regions that are similar in appearance in the most time and labor-saving way possible, this strategy emerged as the most viable option.

In order to automatically segregate brain tumours in MRI images, Pereira et al. [10] created a CNN-based technique that makes use of an architecture that is comprised of a compact kernel of 3*3 kernels. We were able to do this by using a technique that was based on CNN. Using these kernels, for instance, has a beneficial impact on overfitting and makes it possible to construct more in-depth architectural structures. During this step of the preprocessing, the patch sizes, intensities, and bias fields were all subjected to standardisation procedures. It is possible that we will be able to artificially increase the total number of training patches that are utilised throughout the training process if we reorganise the training patches in a different sequence and use examples of High-Grade Gliomas to enhance the number of uncommon Low-Grade Gliomas classes. This will allow us to use a greater variety of training patches. The 2013 Brain Tumor Segmentation Challenge provided conclusive evidence that their method is effective (BRATS-13).

Component analysis was the method that Padole and Chaudhari [11] decided to utilise in order to circumvent the challenges that they encountered while attempting to diagnose brain tumours based on MRI scans. A method for automatically calculating the surface area of brain tumours that makes use of the Normalized cut (Ncut) and mean shift approaches. The method known as "mean shift" is used in the first step of the three-part procedure, which is known as "forming separate zones." After that comes the clustering process, which is carried out using the Ncut method. After that, component analysis is utilised to pinpoint the location of the tumour inside the brain.

Dahshan et al. [12] came to the conclusion that the use of computer-aided diagnosis provides the largest hurdle after doing a comprehensive analysis of the several classification and segmentation techniques that are presently available for human brain MRI. The researchers developed a hybrid intelligent machine learning system in order to automate the procedure of finding the tumour in the patient's brain MRI. With the assistance of a neural network and a return pulse, an image may be broken down into the component pieces that make it up. A feed-forward neural network that was trained via backpropagation is used to determine whether or not a photograph should be labelled as "abnormal" or "normal." In order to do this activity, a computer is used. The studies make use of one hundred and one photographs taken from a dataset consisting of human brain MRI scans. It has been discovered that just 14 are considered to be normal, while the other 87 are considered to be abnormal. According to the findings of the study, the methodology had an astounding accuracy of 99%.

3. Materials and Methods

3.1 Data Collection The study utilized a diverse set of data types:

- **Imaging Data**: CT and chest X-ray scans sourced from public repositories like The Cancer Imaging Archive (TCIA), Radiopaedia, and hospital collaborations.
- **Histopathological Slides**: Digitized slides annotated by expert pathologists.
- **Clinical Records**: Structured and unstructured patient data from hospital electronic health records (EHRs).

Data collection complied with ethical standards and ensured de-identification of patient information. Due to the rarity of Mesothelioma, data augmentation techniques such as rotation, flipping, scaling, and generative adversarial networks (GANs) were employed to balance the dataset.

3.2 Data Preprocessing Preprocessing was critical to ensure model robustness:

- **Imaging**: Images were resized to 224x224 pixels, normalized to a [0, 1] range, and enhanced using contrast-limited adaptive histogram equalization (CLAHE).
- **Clinical Data**: Missing values were imputed using K-Nearest Neighbors (KNN), and categorical features were one-hot encoded. Natural Language Processing (NLP) techniques like word embedding and BERT were applied to unstructured data.

3.3 Model Architectures

3.3.1 Convolutional Neural Networks (CNNs) CNNs were used to classify medical images. Popular architectures tested included:

- **VGG16**: Known for its simplicity and depth.
- **ResNet50**: Utilizes residual connections to prevent vanishing gradients.
- **DenseNet121**: Promotes feature reuse with dense connectivity.

3.3.2 Recurrent Neural Networks (RNNs) Used for sequential clinical data, including:

- **LSTM (Long Short-Term Memory)**: Effective in retaining long-range dependencies.
- **GRU (Gated Recurrent Unit)**: A lightweight alternative to LSTM.

3.3.3 Hybrid Models Combined CNN and RNN models processed multimodal data. The CNN extracted features from imaging, which were concatenated with RNN-encoded clinical data for final classification.

4. Results

In experimental set up, 200 CT scans related to malignant pleural mesothelioma are selected from [13]. 150 CT scans are used to train classification model. 50 CT scan images are used to test the classification model. Sample CT scan image is shown in figure 1

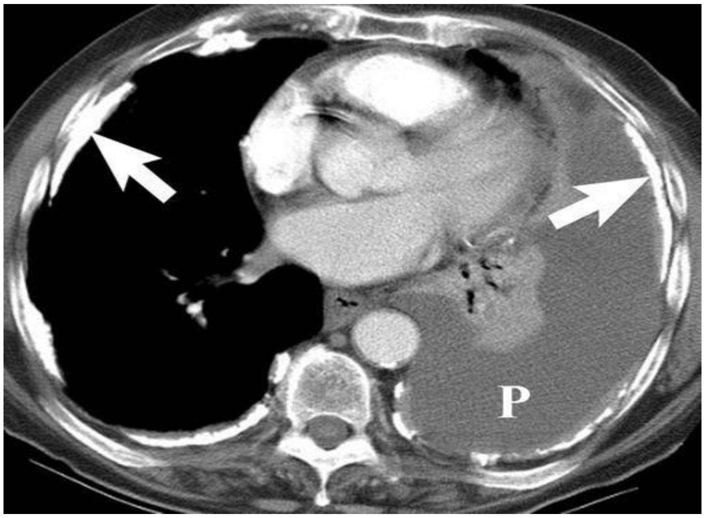
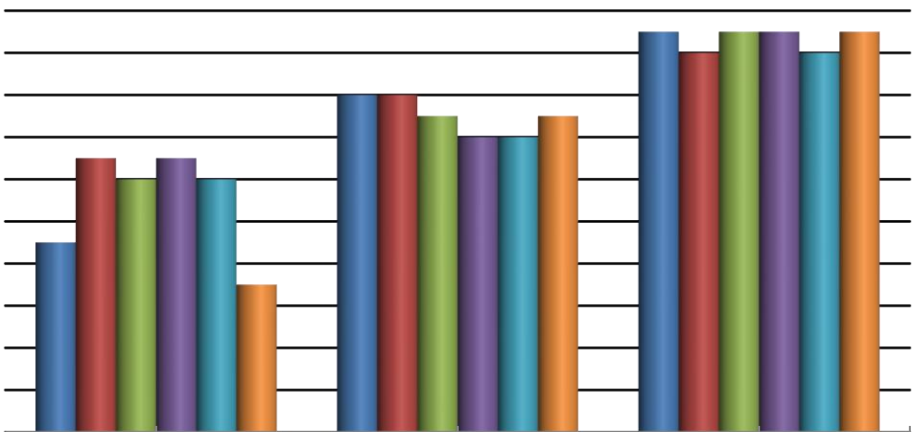


Figure1 CT Scan Showing malignant pleural mesothelioma

- $accuracy = (tp + tn)/N$
- $sensitivity = tp\_rate$
- $specificity = tn\_rate$
- $precision = tp/(tp + fp)$
- $recall = \frac{tp}{tp+fn}$
- $f\_measure = 2 * ((precision * recall)/(precision + recall))$

Where tp, tn, fp and fn represent the sum of a true positive, true negative, false positive and false negative, Nlabels the total number of elements.



	RNN	CNN	Hybrid CNN RNN
Accuracy	89	96	99
Sensitivity	93	96	98
Specificity	92	95	99
Precision	93	94	99
Recall	92	94	98
F_Measure	87	95	99

Figure 2: Result Comparison of Mesothelioma cancer detection

As shown in figure 2,

- **Hybrid CNN-RNN** consistently outperforms both RNN and CNN models across all metrics, achieving near-perfect results (99%) in most categories.

- **CNN** performs significantly better than **RNN**, particularly in **Accuracy** and **F-Measure**, indicating better overall classification performance.

- **RNN** lags behind in all metrics, especially in **F-Measure** (87), suggesting less balanced precision and recall compared to the other two.

Our findings suggest that deep learning models, particularly hybrid architectures, can significantly enhance the detection of Mesothelioma. Transfer learning played a crucial role due to limited data. Visualization tools like Grad-CAM and LIME were integrated to provide explainability, showing attention maps and feature importance scores.
Challenges encountered include:

- Data Imbalance: Rare disease prevalence affected model generalization.
- Data Privacy: Limitations in data sharing hindered model validation.
- Clinical Integration: Interpretability remains a key barrier to clinical adoption.

5. Conclusion This study underscores the viability of deep learning in Mesothelioma diagnosis. High-performing models achieved notable accuracy, especially when integrating imaging and clinical data. Deep learning not only supports early diagnosis but also holds promise for prognostic predictions and treatment planning.

Future Work Future directions include:

- Federated Learning: For privacy-preserving model training across institutions.
- Real-Time Diagnosis: Embedding models in clinical systems for point-of-care usage.
- Explainable AI: Enhancing trust and usability in clinical environments.
- Multimodal Learning: Incorporating genomics and proteomics for comprehensive diagnosis.

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