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| Instructions for Submission: | All files to be uploaded to Moodle separately (Do NOT Zip your submission)  **Expected files : Written report (word document ONLY, No PDF’s),** **Code files (Jupyter notebook)**  **Please upload your Screencast presentation and datasets to Google Drive and ensure the folder is accessible (NOT PRIVATE) and include the drive link in your report** | | |
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**Links:**

1. Data sets link: <https://drive.google.com/drive/folders/14vR5tYSWsYsgFdJVnyZC0jpUiRIW_fi6?usp=sharing>
2. Screencast presentation link: <https://drive.google.com/file/d/1_olo2uQ0HgJyGgC-JSuUINvFKLCyjqUR/view?usp=sharing>

**Big Data Processing for Medical Image Diagnosis: A Deep Learning Approach with Apache Spark**

Sonia Guzman Viloria   
*Msc Data Analyst student*  
*CCT College Dublin*Dublin, Ireland  
2023070@student.cct.ie

Dr. David McQuaid  
Msc Data Analyst Lecturer   
CCT College DublinDublin, Ireland  
dmcquaid@cct.ie

Dr. Muhammad Iqbal  
Msc Data Analyst Lecturer  
CCT College DublinDublin, Ireland  
miqbal@cct.ie

**ABSTRACT**

The integration of deep learning together with big data processing frameworks, such as Apache Spark, holds quite an important promise for fully transforming medical image diagnostics. This paper explores all of the potential of Convolutional Neural Networks (CNNs) in classifying diseases from chest X-ray images and examines just how Apache Spark can be leveraged for processing large-scale medical datasets quite efficiently. The increasing size and the complexity of medical data suppose quite important challenges in the training of deep learning models, making customary methods for data processing and also model training completely insufficient.

This study seeks to increase diagnostic precision using images and workflow speed via merged deep learning and Spark scalability. The study evaluates deep learning architectures, such as CNNs, along with investigating their performance in specific disease classification tasks, such as detecting pneumonia, tuberculosis, along with lung cancer from chest X-rays.

In conclusion, while deep learning and big data analytics offer large transformative potential, their deployment requires overcoming existing limitations. Their successful deployment in clinical settings requires improved model transparency, diverse and high-quality datasets, as well as scalable computational resources.

1. **INTRODUCTION**

The use of artificial intelligence (AI) in medical image analysis has increased dramatically, offering important potential improvement to transform the way medical diagnoses are made. One key AI approach in this field is deep learning. It is capable of automatically learning features from medical images and enabling high levels of diagnostic accuracy. Among all of the various deep learning models, CNNs have emerged as the single most effective way for image-related tasks such as classification, detection, and also segmentation. These networks have shown impressive results within applications such as detecting diseases in medical images, especially in areas wherein manual diagnosis can be time-consuming, expensive, and prone to error.

However, the medical field, especially in diagnosing of diseases from off chest X-rays, presents certain challenges. While the application of deep learning specifically for disease classification using medical imaging has indeed shown outstanding potential, important hurdles still remain, particularly in light of the growing size of medical datasets. For deep learning models to be effective, chest X-rays and other medical images need a lot of data. However, these datasets are quite often noticeably scarce in quantity as well as imbalanced, and this limits the ability of models to generalize across particularly diverse patient populations along with healthcare systems.

In response to all of the massive data requirements, big data frameworks such as Apache Spark have fully emerged as true solutions that do enable the processing of very large medical datasets in a fully distributed and quite efficient manner. Spark provides a scalable platform particularly for data processing; it also allows for faster model training and inference. Thus, Spark addresses the various challenges of working with large medical datasets..

This work explores the possibility of combining deep learning along with big data tools for medical image sorting, especially looking at chest X-ray illness sorting using Apache Spark. By carefully and properly leveraging all of the power of deep learning models, like those CNNs, in addition to all of the scalability of Spark, this work fully aims to substantially improve diagnostic accuracy and greatly improve workflow efficiency. This work also seeks to comprehensively address all limitations within current healthcare practices.

**Objective Statement and Research Question**

The objective of this study is to examine the combination of deep learning methods, notably CNNs, and Apache Spark to classify diseases using chest X-ray images. The study will evaluate fully the effectiveness of deep learning models in classifying quite a variety of diseases, such as pneumonia, tuberculosis, along with other pulmonary diseases, using truly large-scale medical imaging datasets processed efficiently by Apache Spark.

* Howcan deep learning models, when fully combined with Apache Spark's big data capabilities, improve also the classification accuracy and efficiency of disease diagnosis in those chest X-ray images?

Secondary research questions:

1. What are the key challenges in association with the use of deep learning for medical image classification?
2. How can Apache Spark ease the actual handling and subsequent processing of large-scale medical datasets, and what specific advantages does this actually provide in the training of deep learning models?
3. What specific limitations and ethical considerations arise when implementing deep learning for medical diagnosis in clinical settings?

**Presentation of State of the Art**

The application of deep learning in the field of medical image classification has seen meaningful growth in recent years. CNNs are now the main structure for tasks using images because they can automatically learn features from images without needing feature extraction done manually. These networks have shown such outstanding success in various domains of medical image analysis, along with radiology. They have also been quite successful in dermatology and pathology.

Several investigations have shown how well CNNs can work at finding ailments using scans.

* Esteva et al. (2017) achieved human-level accuracy in diagnosing skin cancer using a CNN-based model. This presents the potential of CNNs in dermatological diagnostics.
* Rajpurkar et al. (2017) carefully trained a CNN on a large dataset of chest X-rays in order to properly classify diseases such as pneumonia, tuberculosis, and also lung cancer. Their model achieved similar performance to radiologists, showing the potential capability of CNNs in chest X-ray classification.

Beyond CNNs, transfer learning is now a favored approach to analyzing medical images. Transfer learning entails using a pre-trained model upon a large-scale dataset, such as ImageNet, and then fine-tuning it on a specific medical dataset. This approach reduces, of course, the need for wide-ranging labeled medical data as well as enables models to benefit quite well from the knowledge embedded within large pre-trained networks.

He et al. (2016) introduced the ResNet architecture, which then employs residual connections so as to allow for deeper networks ultimately to be trained effectively. ResNet has been widely used in medical image classification tasks. This also includes the analysis of chest X-rays, due to its specific ability for truly learning high-level features from quite complex images.

Huang et al. (2017) showed in detail the use of DenseNet, a deep learning model that improves much on regular CNNs via connecting each layer to each single layer, thus allowing for better feature reuse and improved performance in medical image tasks.

**Big Data Frameworks: Apache Spark**

While deep learning has demonstrated its value for medical images, a key obstacle involves the large datasets needed for model training. Big data frameworks like Apache Spark provide a solution to this issue by enabling of distributed processing across of large datasets. Apache Spark is a well-known framework that allows for the parallel processing of data, making it an ideal tool for handling wide-ranging medical image datasets that require large computational resources.

Spark helps scalable data processing and also can integrate quite well with deep learning frameworks, like TensorFlow and PyTorch for model training. By parallelizing tasks across multiple nodes within a cluster, Spark accelerates the data preparation process and also reduces all the time required for model training.

Zaharia et al. (2016) further explored the architecture and features of Apache Spark, also highlighting its ability to process massive datasets in a distributed manner. The meaningful flexibility of Spark, along with its natural compatibility to various machine learning libraries, has fully made it a valuable tool for most big data applications, including medical imaging.

Li et al. (2019) applied Apache Spark to preprocess wide-ranging medical imaging datasets. This application enabled the efficient storage and retrieval of image data in a distributed environment, important for large-scale deep learning applications.

**Challenges in Medical Image Diagnosis**

Despite all of the improvements in deep learning for medical image classification, several challenges still remain in the common adoption of AI-driven diagnostic tools in healthcare settings. One of the most meaningful barriers is the complete scarcity of labeled medical datasets. Medical images are often expensive and time-consuming in order to label, and the lack of large, high-quality datasets limits the ability by deep learning models for generalizing across diverse patient populations.

Caruana et al. (2015) explored in depth the complex issue of model interpretability. Additionally, suggested the use of explainable AI (XAI) methods in order to improve transparency and faith in AI technologies.

Ronneberger et al. (2015) did also stress the real importance of fully understanding that decision-making process in deep learning models, particularly in medical applications, to ensure that they truly can be trusted by clinicians.

Data scarcity, model interpretability and computational efficiency are some of the challenges that the AI in medical image diagnosis faces. Federated learning that allows models to be trained on decentralized data without physically sharing sensitive patient information, greatly holds much promise specifically for improving the general accessibility of AI-driven diagnostics while diligently ensuring overall data privacy.

1. **LITERATURE REVIEW**

The convergence of deep learning and big data processing frameworks in medical image analysis, particularly for diagnostic tasks involving large-scale datasets has been revolutionary. This section reviews existing research, exploring the role of certain CNNs for disease detection in chest X-rays as well as the utility of Apache Spark in processing huge medical image datasets efficiently.

**Deep Learning in Medical Image Diagnosis**

The application of multiple deep learning techniques has been a meaningful in medical image analysis, specifically, if CNNs are applied. CNNs, owing to their capacity to autonomously learn layered features from images, have shown outstanding performance in image classification tasks (LeCun, Bengio, and Hinton, 2015). In the context of a chest X-ray analysis, CNNs are particularly quite effective due to their own ability so as to detect patterns in image data, making of them very well-suited for the task of disease classification (Rajpurkar et al., 2017). One study by Irvin et al. (2019) demonstrated that certain deep learning models, specifically CNNs, could classify most chest X-rays at one performance level comparable to many radiologists, with high sensitivity for detecting pneumonia, tuberculosis, and multiple other lung diseases.

Recent improvements in CNN architectures, such as ResNet and DenseNet, have actually greatly improved model performance, particularly with much deeper networks that allow also for better feature extraction and even more accurate classification (He et al., 2016). These models can leverage more residual connections, preventing any vanishing gradient problem and improving on the accuracy of the network. Furthermore, the use of transfer learning with pre-trained networks such as the ResNet and VGG has considerably accelerated the actual development of deep learning models for medical image analysis (Tan et al., 2020). Transfer learning allows for leveraging of existing large datasets, such as ImageNet, to fine-tune models on smaller medical datasets, thus overcoming of the issue of limited annotated medical data.

However, despite all of these improvements, several of the challenges still persist in applying deep learning to a medical image diagnosis. These specific challenges include some data scarcity, the need for quite high-quality labeled data, and interpretability. Annotating medical images is quite labor-intensive along with expensive, limiting the availability of plentiful large datasets for training deep learning models. Furthermore, deep learning models are frequently criticized. This is because they are "black boxes," making it difficult to interpret how the model arrives at a decision. This absence of interpretability constitutes a prominent hurdle for the broad adoption of AI in clinical practice, where model transparency is critical (Samek et al., 2017).

**Big Data and Apache Spark in Medical Image Processing**

Medical imaging generates large volumes of data, which can really be quite challenging to be easily handle with some customary data processing frameworks. To address this very issue, Apache Spark, a fast, in-memory data processing engine, has fully emerged as a influential tool for the processing of large-scale medical image datasets. Apache Spark allows for distributed data processing within multiple nodes, rendering it highly scalable and capable of handling big data, inclusive of medical images necessitating meaningful computational resources (Zaharia et al., 2016).

Wang et al. (2020) examined Apache Spark's utility in preprocessing and analyzing medical image datasets in their study, noting that it can handle a huge amount of data created by medical imaging devices. Spark’s support for distributed computing allows for parallel processing of many images, reducing considerably the total time needed for deep data preparation and model training. This is notably important for deep learning models; along with that, they require large datasets as well as meaningful computational power for their training.

In the healthcare sector, where patient data privacy as well as security are of utmost concern, Apache Spark can also be used in conjunction with privacy-preserving techniques such as federated learning. Federated learning allows for decentralized model training upon respective local data sources, thereby ensuring that sensitive medical data is truly not transferred across various systems, while still greatly benefiting from the overall global learning model (McMahan et al., 2017). This can considerably improve the scalability of AI models. This also respects patient privacy and certain regulatory constraints.

**Challenges and Limitations**

Despite the promising potential of deep learning as well as big data frameworks within medical image diagnosis, several challenges still remain until today. One of the most primary challenges concerns is the limited availability of annotated datasets that are needed for the proper training of deep learning models. Datasets such as ChestX-ray14 (Wang et al., 2017) provide on large-scale labeled medical images, but the quality of annotations can vary, and many conditions are underrepresented, leading to class imbalance. This can negatively affect the performance of models, and this may result in biased predictions.

Data privacy and security are also large concerns in medical image analysis, particularly when working with sensitive patient data. Several studies have highlighted the need for secure data sharing protocols in addition to the development of privacy-preserving models. That is done to ensure that patient information is comprehensively protected during the training of AI models (Raji and Buolamwini, 2019).

Another limitation for applying deep learning in medical image analysis is just the issue of model interpretability. While CNNs have shown superior performance in classification tasks, clinicians as well as healthcare practitioners require models that they can understand and fully trust. Several studies have indeed proposed methods for further improving model transparency, such as those attention mechanisms and also saliency maps, which truly can help to visualize what parts of an image contribute to the model’s overall decision-making process (Selvaraju et al., 2017).

**Future Directions and Emerging Trends**

Upcoming studies merging from machine learning with large datasets must center on some main subjects. A key direction involves improving the overall generalizability of deep learning models for diverse healthcare settings. Even though deep learning models have still achieved high accuracy on standard datasets, their performance may degrade badly when applied also to real-world data due to some variations within imaging quality, patient demographics, and even healthcare infrastructure (Liu et al., 2019).

To address this issue, there is an increasing emphasis on multi-center as well as multi-modal data collection, which can provide more diverse and representative datasets for training. The important development of standardized datasets and benchmarks for medical image analysis might occur. It will be vital in ensuring that deep learning models are quite strong and also can be deployed effectively in diverse healthcare environments.

Another meaningful direction is the use of explainable AI (XAI) techniques to improve model interpretability. By providing further understandings into just how models make predictions, XAI can then help to build trust with the clinicians and ensure that deep learning models truly can be integrated into clinical workflows. Many studies have proposed using attention maps along with gradient-weighted class activation maps (Grad-CAM) for visualizing the regions within an image influencing model predictions (Chattopadhay et al., 2018).

Additionally, there is a growing enthusiasm for employing transfer learning and few-shot learning methods to surmount the problem of scarce labeled data. Transfer learning fully allows models to leverage pre-trained weights from datasets, while few-shot learning aims to train models with data by generalizing from examples (Chen et al., 2020).

This literature review aim to highlight the very transformative potential of deep learning and also big data frameworks, such as Apache Spark, in the broader field of medical image analysis. While deep learning models, particularly CNNs, have demonstrated extraordinary performance in chest X-ray classification, several difficulties remain, including data scarcity, model interpretability, as well as privacy concerns. The particular ability of Apache Spark to adequately handle quite large-scale medical image datasets efficiently, coupled with particularly emerging techniques such as federated learning and explainable AI, holds genuine promise for fully overcoming all of these challenges. Moving forward, both cross-disciplinary research and collaboration will be important in dealing with these limitations. This dual effort ensures the successful integration of AI-driven diagnostic tools into clinical practice.

1. **CRITICAL EVALUATION**

The integration of deep learning models alongside with big data processing frameworks like Apache Spark has become increasingly important for advancing through the field of medical image analysis. While all of the reviewed literature presents several quite promising findings regarding the application of CNNs in the diagnosing of medical conditions from chest X-ray images and the utility of Apache Spark in the handling of large datasets, it is important to analyze and evaluate all these studies by considering their potential implications, natural limitations, and potential contradictions. This evaluation will highlight all the strengths as well as all the weaknesses of the approaches. It will draw attention to research gaps, also suggesting directions for future work.

**1. Performance of Deep Learning in Medical Image Diagnosis**

The primary finding resulting from the literature on deep learning in medical image diagnosis is the outstanding performance of CNNs, especially for tasks such as detecting pneumonia, tuberculosis, along with other pulmonary diseases from chest X-rays. Rajpurkar et al. (2017) showed that CNN models could perform as well as humans at classifying images, which has major implications for how diagnoses are done. Certain AI systems such as CheXNet (Rajpurkar et al., 2017) have been shown to potentially outperform radiologists in specific tasks, thereby suggesting the overall potential for deep learning in order to improve the diagnostic accuracy, reduce the human error, and further improve the efficiency of the medical professionals.

However, these particular results do also come along with limitations. While deep learning models have been successful within highly controlled settings, their performance in the inside real-world clinical environments remains inconsistent. One of the primary limitations includes a dependency on quite large datasets. These datasets must be well-annotated. As pointed out so clearly by Irvin et al. (2019), the performance of certain deep learning models considerably degrades when tested on data. That data differs from the training set in various terms of quality, demographics, and imaging protocols. This finding suggests that while deep learning can work effectively in a controlled laboratory setting, its generalizability to diverse clinical settings is still as an unresolved challenge.

Furthermore, how CNN models are interpreted is still a key issue. Although deep learning models have usually been shown to perform well in classification tasks, they are often regarded as "black boxes." This certain lack of transparency throughout decision-making processes is a major concern for healthcare practitioners who commonly rely on understanding the rationale behind a diagnosis, especially during the times it comes to complex decisions involving patient care. As Samek et al. (2017) sharply highlight, the interpretability issue is a major barrier to the adoption of AI-driven diagnostic tools in clinical practice, in which trust in the technology is primary. Methods such as both Grad-CAM and also attention mechanisms (Selvaraju et al., 2017) attempt to address this issue, but they still are in early stages in development and often lack the robustness which is required for common use within critical applications.

**2. Big Data Processing with Apache Spark**

Apache Spark has gained recognition for its potential to process significant amounts of medical image data rapidly. The utilization of Spark for sizable big data processing in healthcare can substantially reduce the total time required in the context of image preprocessing, training, as well as inference. As highlighted indeed by Wang et al. (2020), Spark’s distributed computing capabilities allow specifically for the parallel processing of large datasets, which is particularly necessary when working carefully with the enormous amounts of data generated routinely by modern medical imaging technologies. The specific ability to readily handle truly large-scale datasets, without overly overwhelming all computational resources, subsequently makes Apache Spark an exceptionally attractive tool for various healthcare institutions actively dealing with particularly big data.

Nonetheless, although Apache Spark is very promising for medical imaging data, combining it with deep learning models poses some difficulties. One major limitation is from the lack of native support for real-time processing of deep learning models. Although Spark does batch processing well, real-time or almost real-time inference, often needed for quick diagnoses within clinical settings, is still difficult. Deep learning image processing in real-time needs frameworks handling computational loads and the demand for rapid decisions. As a result, integrating of deep learning frameworks like TensorFlow or PyTorch with Spark for real-time inference continues to pose technical challenges (Zaharia et al., 2016).

**3. Ethical and Privacy Considerations**

One key issue in applying deep learning specifically to medical image diagnosis is certainly ensuring patient data privacy. Another important issue involves the security of patient data. McMahan et al. (2017) discussed one potential aspect of federated learning. It is a distributed learning technique that allows some models to be trained on decentralized data while still keeping sensitive information on the local devices. This approach promises to reduce privacy concerns by ensuring that patient data does not need to be shared or stored centrally. This minimizes the risk of data breaches.

Despite all of the promising potential with federated learning, there are still several concerns that do remain unaddressed. For example, many federated learning systems remain susceptible to adversarial attacks, through which malicious actors could easily manipulate local data by model updates. Furthermore, even though federated learning can protect data privacy, it still does not eliminate the need for strong data governance and compliance with regulations such as the General Data Protection Regulation (GDPR) and Health Insurance Portability and Accountability Act (HIPAA). Researchers must certainly address these legal and regulatory difficulties to ensure that AI systems in medical image diagnosis can operate within the boundaries of law and ethics.

**4. Research Gaps and Contradicting Viewpoints**

There are still several research gaps that require further exploration. One such gap really is the issue of model generalization. Several deep learning models achieve superior performance on typical datasets, but they frequently fail when deployed within real-world clinical settings. Ensuring AI models generalize across hospitals, regions, along with various patient demographics is a challenge. This issue truly remains a critical hurdle (Liu et al., 2019). Future research must focus on developing additional strong and flexible models that can handle variations in medical images and patient populations.

One other specific area which requires additional, deeper investigation is the full integration of certain big data frameworks along with existing AI models in current real-time clinical decision support. While Apache Spark surely has proven quite effective for large-scale data processing, real-time AI inference specifically in healthcare settings still remains quite a challenge. There is indeed an important need for further research into optimizing distributed deep learning models specifically for such real-time applications, so as to ensure that those AI-driven diagnostic systems are able to provide more timely and accurate results specifically for clinicians.

Additionally, the further use of explainable AI (XAI) techniques, such as saliency maps and attention mechanisms, is indeed still in those early stages. While these methods have shown promise in improving upon model interpretability, they are not yet widely used in clinical settings. Additional study is vital for creating more user-friendly, efficient methods of conveying deep learning model decisions to doctors. Improving model transparency will be vital in securing trust and ensuring AI tools are integrated into clinical workflows.

**5. Implications for Future Research**

The reviewed studies have demonstrated that deep learning, in combination with big data frameworks like Apache Spark, holds outstanding potential in improving medical image diagnosis. However, many key challenges must be addressed. Likewise, various limitations must be addressed before AI-driven diagnostic systems can be fully integrated into clinical practice. These challenges include model generalizability with interpretability, privacy concerns of real-time inference, and the integration in data. Furthermore, research gaps related to bias, diverse datasets, along with model robustness remain unresolved.

1. **CONCLUSIONS**

The integration of deep learning along with big data frameworks such as Apache Spark has demonstrated meaningful potential in transforming the way medical image diagnosis are executed. This study explored the role of CNNs within medical imaging, focusing on their application in classifying chest X-ray images, in addition to reviewing how Spark enables efficient large-scale data processing. The literature review highlighted the growing reliance upon AI-driven diagnostic tools, showing their capacity to achieve or exceed human-level performance in many medical imaging tasks.

Notwithstanding each and all of these various improvements, truly meaningful challenges still persist. The constant reliance that we have upon large, annotated datasets still remains as a major limitation, as medical imaging data is often quite scarce and even difficult to obtain. Additionally, deep learning models suffer from interpretability issues; increasing the concerns regarding their reliability and adoption in clinical work. Computational constraints obstruct the adoption of AI-driven diagnostic systems. This is especially true in resource-limited healthcare settings. Furthermore, ethical considerations, such as bias in the AI models along with patient data privacy, must be mindfully addressed before these technologies are able to be fully integrated into healthcare workflows.

A critical evaluation of each of the existing research studies revealed some gaps that existing models as well as the need for a much more strong clinical validation. Although CNN-based models have demonstrated such high accuracy within controlled experiments, their specific real-world performance remains uncertain due to variations within imaging techniques, for particular patient demographics, and from adequate healthcare infrastructure. Additionally, while Apache Spark provides a specific solution for great data processing, optimizing it during real-time AI inference remains a perpetual challenge.

Future research certainly should prioritize the improvement of AI model interpretability via explainable AI (XAI) techniques, carefully developing standardized and also diverse medical datasets, as well as leveraging federated learning for improving data privacy. Furthermore, several key improvements that exist in distributed deep learning frameworks should mainly focus on completely reducing computational overhead in order to make AI-driven diagnostics greatly more accessible to most healthcare facilities worldwide.

In conclusion, although deep learning and big data analytics present such a transformative opportunity for medical image diagnosis, still their successful implementation in clinical settings requires properly dealing with all current limitations. By the refining of AI algorithms and also through improving of data accessibility, the healthcare industry can harness a greater potential of such technologies. By ensuring ethical considerations, the healthcare industry has the potential to vastly increase patient outcomes and diagnostic accuracy to a much greater extent.

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