The Use of Machine Learning Methods for Image Classification in Medical Data

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Abstract

Integrating medical imaging with computing technologies, such as Artificial Intelligence (AI) and its subsets: Machine learning (ML) and Deep Learning (DL) has advanced into an essential facet of present-day medicine, signaling a pivotal role in diagnostic decision-making and treatment plans (Huang et al., 2023). The significance of medical imaging is escalated by its sustained growth within the realm of modern healthcare (Varoquaux and Cheplygina, 2022). Nevertheless, the ever-increasing volume of medical images compared to the availability of imaging experts. Biomedical experts and radiologists have resulted in a widening disparity, causing an excess and overwhelming workload on these healthcare professionals (Chen et al., 2021). Several studies indicate that the present-day biomedical radiologist is now saddled with the daunting task of interpreting an image almost every 10 seconds to keep pace with the burgeoning clinical demands (McDonald et al., 2015; Hosny et al., 2018; Lantsman et al., 2022). This cognitive drain has invariably led to inevitable consequences such as delays in diagnosis and an amplified risk of diagnostic errors – thus, the biomedical imaging aspect is in dire need of methods that would aid accurate diagnostics and analytics for improved decision making. In this review, the importance of AI-related technologies such as ML and/or DL methods are reviewed in relation to the processing of medical or biomedical images along with their potentials, challenges, and possible suggestions for future studies in the health landscape. The focus will be on machine learning methods associated with the medical field of image classification.

2. Background and Literature Review

In the past few years, there has been a growing trend in the application of ML techniques for image classification in medical data. Since Machine and Deep learning were developed, image classification accuracy has greatly increased. Amplifying this growth, Weibin et al. (2019) particularly noted an emphasized the shift in paradigm for image classification, as a result of the application of machine learning techniques that escalate the process of determining patterns, structures, and anomalies in medical images. In their emphasis, the automation of the manual imagery processing for biomedical experts and radiologist has enhanced accuracy in diagnosis and effectiveness in classifying medical images such as MRI, brain, spine, etc. via the integration of AI-related technologies known as ML. Supporting the perspective of biotech image classification and also considering the imperious landscape of timely and accurate diagnoses, Varoquaux and Cheplygina, (2022) pointed out the existence of an unrelenting need to seamlessly integrate technology-based systems such as AI and its subsets into the medical imaging workflow. Such integration holds the promise of not only alleviating the associated with the classification and analysis of medical imaging but also enhancing the overall efficiency and precision of the diagnostic process in future time.

The use of ML and DL in the medical field of image classification has to a greater extent shown revolutionized growth in the public health landscape, particularly for image diagnosis, analysis, and computer vision (Chen et al., 2021). Its wide adoption and application in several domains have impacted changes in the way data is being processed and presented across the health sectors. (Varoquaux and Cheplygina, 2022). Machine learning algorithms are used in the classification of medical images into various categories of disease and can also be used to optimize the next step of the diagnosis. In the context of medical data, medical imaging is seen as “sets of procedures used to acquire clinically meaningful information from techniques, commonly for diagnosis or prognosis” (Surendar and Shital, 2019). Adding to this conception, Meghavi and Megha (2022) further explained that medical images are considered as “actual origin of appropriate information required for disease detection” “. On the construct of image classification, Weibin et al. (2019) connoted and emphasized it to be the series of procedures involved in assigning an image to one or more labels. In this sense, image classification is seen as a core task for computer vision (CV) which is facilitated by supervised learning methods where trained data are classified into predefined classes during the training phase (Hosny et al., 2018; Sarker, 2021**).**

The path of ML in medical imaging not only projects its proficiency but also emphasizes its pivotal role in the realization of the broader ambitions established forth by early proponents of AI in several domains of medicine (Hosny et al., 2018). The convergence of technological advancements, clinical practices, and the overarching vision of AI in medicine positions the application of ML methods as a transformative key to unearthing unparalleled diagnostic precision and efficiency (Acito, 2023). Thus, the building blocks of AI and its subsets ML or Dl are the models, techniques, algorithms, or methods driving its support for a variety of application in the medical field. For medical imaging or precisely image classification, several ML methods exist and several studies within the past decade have reviewed a plethora of theses methods in different medical domains (Hosny et al., 2018; Ghosh et al., 2019; Che et al., 2021, Chen et al., 2022; Acito, 2023; Huang et al., 2023). There are various machine learning methods used for image classification. They are discussed succinctly in subsequent section.

3. Machine Learning Methods and Image Classification

1. **Convolutional Neural Network (CNN):** O’Shea & Nash (2015) defined CNN as a network that is comprised of neutrons that are self-optimized through learning”. The primary usage of CNN is in the field of pattern recognition within images (Keiron & Ryan, 2015). Ghosh et al., (2020) defined CNN as “a special type of multilayered neural network inspired by visual system”. CNN is applied in a wide range of fields which includes: image classification, text recognition, action recognition, image caption generation, medical image analysis, security and surveillance, automatic colorization of image and style transfer, and satellite imagery (Ghosh et al., 2020). The CNN comprises two main layers, the convolutional layer and the pooling layer.
2. **Support Vector Machine (SVM)**: The SVM is a ML method that support the classification of medical image, which is employed by locating a hyperplane that totally separates two classes of data. It presents results in high accuracy and very suitable for handling large datasets because of its ability to handle non-linear data and its high spatiality (Zhang, 2011).
3. **Decision Tree (DT):** This ML method is a popular non-parametric supervised learning technique used for both regression and classification tasks (Sarker, 2021). It supports a tree-like interpretation of automated imaging outcomes.
4. **K-Nearest Neighbors (K-NN):** the KNN method is a supervised ML technique of classifying medical image that is simple and effective (Acito, 2023). Utilizing pixel values or extracted characteristics, the KNN compares the similarity of images to classify them. Ranjan et al., (2019) noted that the KNN is “one of the better methods when there is no proper knowledge about the distribution of incoming data”. The KNN is also used in regression tasks. The major drawback of KNN as identified by Acito in 2023 is that “each time a new observation needs to be classified, a routine scan of the training data is conducted hence, it can be time-consuming for larger datasets”.
5. **AdaBoost**: This is called Adaptive Boosting. Tharwat (2018) indicated that the main objective of the AdaBoost method is to “improve the performance of different weak classifiers”.
6. **Naïve Bayes**: the Naïve Bayes methodology has gained popularity because of its “incremental learning characteristics of integrating prior knowledge. One major advantage of this method is that it only needs to estimate the required parameters based on few amount of training data. Applications of the Naïve Bayes method include areas in clinical medicine, telecommunication,

gene technology, precision instruments, linguistics, and artificial intelligence" (Chen et al., 2021).

7. **Recurrent Neural Network (RNN)**: these are supervised learning methods that comprise of artificial neurons with one or more feedback (Salehinejad et al., 2017).

Each of these methods is potentially effective and defective in different aspects of managing medical data. By potentials in accurately classifying images, three of these ML methods or techniques trend the chart according to some studies: CNN, SVN, and RF (Ghosh et al., 2020; Sarker, 2021; Chen et al., 2022; Acito, 2023). Based on the research and analysis conducted by various researchers, the CNN method is considered the most used method of image classification. CNN was proven to have very high performance with very high accuracy, Taner et al., (2021) concluded that CNN has "gained great popularity as an effective method for classifying images and has received much more attention than other machine learning algorithms". **4. Challenges Associated with the Use of ML Methods for Medical Data Classification**

The methods or techniques linger for the use of ML and DL in the classification of medical data and it has improved the diagnosis, processing, and analysis of medical images via computer visions and other forms of AI. However, these technologies are not without challenges and according to some studies, there have been failures leading to causality issues with the use of these technologies (Taner et al., 2021; Chen et al., 2022; Huang et al., 2023). Transparency as an issue was frowned upon by Chen et al. (2022) because the use of ML techniques hides the process from the users and thus, the relationship between the methods and biomedical experts is vague in the classification of medical data. Another threat to this intervention for image classification in the medical landscape is the causality burden in medical imaging as expressed by Castrol et al. (2020). This challenge is associated with the annotation of images and their causal relationships when classified with automated methods like ML or Dl techniques. This lack of transparency amounts to the "scarcity of high-quality annotated data and mismatch between the development dataset and the target environment". If not considered, it may lead to poor semantic insights on decision-making by radiologists and other image professionals. Finally, most ML methods are customary to datasets and domains leading to poor performance outside the domain of applicability.

Possible recommendations for these identified challenges and future guides suggest that:

- For consistency in domain volatility, improvement can be done by developing transfer learning approaches where pre-trained learning models are fine-tuned on the target dataset. This would increase the applicability of ML methods with accuracy across domains.
- To enhance transparency between the ML methods and image annotation processes or procedures, causal reasoning or theory is advised. This may provide more insights for users via an explainable medical imagining perspective.
- The integration of self-supervised learning methods into image classification appears as a promising and strategic solution to surmount the inherent complexities associated with the curation of largescale annotations in the medical community. In the aspect of medical image classification, the selfsupervised learning paradigm offers a compelling avenue to evade the resource-intensive task of producing meaningful representations using unlabeled data. By this concision, leveraging inherent structures and relationships within the data itself can empower machine learning methods to autonomously learn meaningful representations, alleviating the dependency on methodically annotated datasets. This not only addresses the challenges posed by the dearth of annotated medical images but also holds the potential to significantly augment and improve the robustness of the classification methods within the medical imaging domain.
- On a final note, an empirical study is needed to establish further the effectiveness of these ML methods and their application in actual medical data image classification.

5. References

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