A Comprehensive Review on Biomedical Image Classification using Deep Learning Models

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Received: 13 August 2024 | Revised: 15 October 2024 | Accepted: 29 November 2024

 DOI: https://doi.org/10.48084/etasr.8728

ABSTRACT

Medical imaging is one of the most efficient tools for visualizing the interior organs of the body and its associated diseases. Medical imaging is used to diagnose diseases and offer treatment. Since the manual examination of a massive number of Medical Images (MI) is a laborious and erroneous task, automated MI analysis approaches have been developed for computer-aided diagnostic solutions to reduce time and enhance diagnostic quality. Deep Learning (DL) models have exhibited excellent performance in the MI segmentation, classification, and detection process. This article presents a comprehensive review of the recently developed DL-based MIK classification models for various diseases. The current review aims to assist researchers and physicians of biomedical imaging in understanding the basic concepts and recent DL models. It explores recent MI classification techniques developed for various diseases. A thorough discussion on Computer Vision (CV) and DL models is also carried out.

Keywords-medical image analysis; computer-aided diagnosis; imaging modalities; deep learning; computer vision

I. INTRODUCTION

Biomedical imaging is considered the most significant tool commonly utilized for diagnosing and analyzing various diseases [1]. Doctors examine the images to comprehend the source and type of a disease. MI analysis has demonstrated the advantages of applying pattern analysis techniques, digital image processing, and CV, such as adding objective strength and enhancing diagnostic confidence via quantitative analysis [2]. All types of new medical imaging equipment are popular with the progression of medical treatment [3]. The kinds of medical imaging broadly utilized in clinics are mainly Positron-Emission Tomography (PET), Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Ultrasound Imaging (UI), and X-ray. Additionally, biomedical imaging contains certain common RGB imagery, such as fundus retinal and microscopy images [4]. Clinicians utilize CT and other medical imagery to find out the condition of patients, which has turned out to be the main basis for the clinical diagnosis of doctors [5]. Thus, the study of MI processing is becoming the main focus in the CV field.

Automatic MI analysis may minimize the workload of radiologists and pathologists. Also, it offers accurate diagnoses and hastens the diagnosis process [6]. DL and Machine Learning (ML) techniques have been commonly utilized for automatic MI processing [7]. ML has pointedly impacted healthcare delivery and medical research. However, the efficiency of ML methods for image processing depends on feature extraction systems, while an expert is needed to choose the most valuable features for the specific task. ML techniques process images in 2 phases [8]. In the first phase, a hand-crafted feature extracted technique extracts significant features from the images. Next, a classifier model categorizes the images. Therefore, utilizing ML techniques in MI analysis is often time-consuming and tedious [9]. DL techniques have surpassed ML methods in MI analysis tasks. DL methods can automatically extract image features, which makes them more appropriate for automatic MI analysis, rendering precise diagnoses [10]. Regarding image processing, DL methods are utilized to train methods for automatic detection of objects by examining lots of images.

New DL MI categorization models for a range of disorders are extensively covered in this paper. The purpose of the current review is to provide biomedical imaging researchers and doctors with a better grasp of the fundamental ideas and the latest DL models and methods for disease-specific biomedical image classification are covered. In order to emphasize the analyzed techniques' distinctive features, a comprehensive comparison analysis of the examined methods is conducted. Lastly, the CV and DL models are thoroughly discussed.

II. REVIEW OF THE RECENT LITERATURE

Authors in [11] presented a complete analysis of the current Deep Neural Networks (DNNs) research direction implemented in MI analysis. Pathological and clinical analyses were presented using a selective patch of the most cited studies. It was demonstrated how DNN can manage medical complications, namely segmentation, classification, localization, automatic diagnosis, and detection. The employed datasets included a range of imaging technologies, such as, Fluorescence Angiography, X-ray, CT, Ultrasound (US), and MRI. The particular study reviewed diverse paradigms of DNN and focused on Convolutional Neural Networks (CNNs), which rendered an outstanding percentage of solutions associated with other DNN frameworks. Authors in [12] analyzed DL-related techniques for multimodal MI-segmented tasks. Various DL network structures were presented, the proposed fusion approaches were subsequently examined, and the derived outcomes were compared. Authors in [13] attempted to conduct a complete review of CNN applications in MI analysis. The main purpose was to inspire MI analysis researchers to extensively implement CNNs in their diagnosis and research. A brief introduction to CNNs was also given in this study. The major medical image analysis errands, like localization, image classification, detection, and segmentation, were presented. In [14], the basic principles of DL techniques were deliberated, in addition to an outline of DL successful applications, including image segmentation for diverse medical applications. Finally, certain research problems were emphasized, and the forthcoming need for further enhancements was pointed out. Authors in [15] summarized and reviewed some studies to offer a complete overview of implementing DL techniques in numerous medical image analysis errands.

A review of the existing disease diagnosis models for the stomach, neuro, retinal, pneumonic, bosom, brain, computerized pathology, heart, bone, musculoskeletal, and breast regions was carried out in [16]. Knowledge-based prediction, information exploration, knowledge deployment, and DL networks were successfully implemented in big data. Authors in [17] attempted to offer a complete review emphasizing multi-organ image segmentations, which can be critical for radiotherapy, where cancer and organs at risk should be contoured for treatment planning. They grouped the investigated techniques into two comprehensive classes, i.e. "end-to-end segmentation" and "pixel-wise classification." Table I depicts the outline of the existing reviews.

The main contributions of the present paper are: (1) It provides a comprehensive review of the latest DL models applied to biomedical image classification. With the purpose of offering a detailed overview of recent advancements in the field, it helps both researchers and practitioners understand how DL can be applied to medical imaging tasks, including disease diagnosis and treatment planning. (2) It provides a structured comparison of various DL techniques for biomedical image classification, serving as a valuable resource for researchers by highlighting the strengths, weaknesses, and potential of different models, thus, guiding future research. (3) It includes practical insights for academics who are looking to implement DL models in clinical applications. (4) It provides a detailed review of recent DL-based biomedical image classification methods, identifying gaps in existing research, and proposing possible directions for future work. By doing so, it aims to serve as a foundation for both advancing DL methodologies and more effective applications of them in healthcare. The new insights in the current paper involve identifying key trends and innovations in DL for biomedical imaging, such as the increasing use of transfer learning, multi-modal image fusion, and new architectures that address specific challenges in medical image analysis, like handling 3D and high-resolution images. It also highlights areas where DL can be further optimized, such as enhancing segmentation accuracy and reducing computational costs.

III. DL-BASED BIOMEDICAL IMAGE ANALYSIS

The count of publications executing CV systems to static medicinal images has recently developed from 100 to 1000 [18]. Several areas, such as radiology, ophthalmology, pathology, and dermatology, have obtained substantial attention because of the visual pattern-detection nature of analytic errands under this specialty and the developing accessibility of extreme infrastructure imageries. The single features of medicinal image posture constitute a number of problems in DL-based CV. Initially, the images are enormous. The digitized histopathology slides take gigapixel images in which classical CNN image input can be approximately only 200 × 200 pixels.

Additionally, distinct chemical arrangements render distinct slides to similar pieces of tissues, and various digitized devices or settings can generate distinct images to similar slides. The radiology modalities like MRI and CT render equivalent huge 3-D images, forcing typical CNNs for both to work with groups of 2-D slices or alter their internal infrastructure for processing in 3-D [19]. Also, the US renders a time series of noises, such as 2-D slices of 3-D context–slices that can be spatially connected but not allied. DL begins with a reason for a single problem with medicinal information. For example, Multiple-Instance-learning (MIL) allows learning in databases comprising huge imageries and some labels. The 3-D convolutional in CNN can allow optimum learning in 3-D volumes, such as CT and MRI [20]. The spatial-temporal method and imagery registration enable using time-series imagery, like US.

CV in medicinal modalities with non-standardized data groups needs a CV combination to present physical models. For instance, in otolaryngology, CNNs support first-aid medical doctors in managing patients' noses, throats, and ears [21], as well as over-mounted devices connected to smartphones. Serology and hematology are advantageous in microscope-integrated AIs, which analyze general conditions or the number of blood cells in several categories; repetitive tasks that can be increased with CNNs. In gastroenterology, AI has established stunning abilities. Video-related CNNs are combined as endoscopic processes for scope guidance, lesion recognition, and lesion analysis [22]. Their application includes esophageal and gastric cancer screening, identifying stomach infections, like H. Pylori, and even determining hookworms. The researchers took this domain one step further by generating whole medicinal AI devices such as the home smart toilets set with analytic CNN on cameras. Besides investigating disease states, CV assists human health and welfare with applications like screening human embryos. Concerning CV application in radiology, it is evident that it has rapidly burgeoned as a research field, developing a corpus of works that covers every modality with a concentration on MRI, X-rays, and CT. The Chest X-ray (CXR) examination, a key medical concentration region, is an exemplar. Studies of brain images, especially for time-critical cases of stroke, and abdominal images have likewise obtained substantial attention [23]. The disease classifier, nodule recognition, and region segmentation (viz., ventricular) approaches are established for most data collection proceedings. The domain endures expanding, with effort being put in image translations (for instance, replacing noisy US images with MRI), image rebuilding and improvement (i.e., transforming lower-dosage and lower-resolution CT imageries to higher-resolution imagery), automated report generation, and temporal tracks (for instance, image detection for tracking tumor development in time).

IV. REVIEW OF EXISTING BIOMEDICAL IMAGE CLASSIFICATION MODELS ON VARIOUS DISEASES

A detailed comparison study of the reviewed approaches is made to highlight the unique characteristics of each technique. Figure 2 shows the systematic process involved in the survey of DL-based medical data classification models.

A. *Brain-Related Diseases*

In [24], AI methods were devised to enhance the precision of MIT inverse issues. Four DL networks, which involve a Stacked Autoencoder (SAE), Restricted Boltzmann Machine (RBM), Denoising Autoencoder (DAE), and Deep Belief Network (DBN), were utilized to find a solution to the nonlinear reconstruction issue of MIT, and the back-projection algorithm and reconstruction outcomes of DL networks were compared. Authors in [25] proposed a concatenation technique and multi-level feature extraction for the initial identification of Brain Tumors (BTs). Initially, the attributes from distinct Inception modules were derived from the pre-trained Inception-v3 method and concatenated such features for BT categorization. Pre-trained DensNet201 was utilized to extract features from several DensNet blocks. After that, the attributes were concatenated and transferred to the softmax classifier for BT classification.

TABLE I. SUMMARY OF THE EXISTING SURVEYS

Ref.	Title	Year	Objective	Merits	Limitations
[11]	Effectual DNN models for medical image analysis	2022	Explore DNN models for examining medical images.	Discussed data augmentation, limitations of DNN training, and execution time.	Only focused on DNN, performance evaluation is missing.
[12]	A review: DL for medical image segmentation using multi-modality fusion	2019	Investigate multimodal images for the segmentation process.	Effective results under multimodal fusion.	There is little detail about DL. Performance evaluation is missing.
[13]	CNNs in medical image understanding: a survey	2022	Discuss CNN models for interpreting medical images.	Focused on multiple organs.	Requires improvement in the learning process.
[14]	DL approaches to biomedical image segmentation	2020	Explore DL models to segment medical images.	Detailed review of various medical applications and modalities.	Performance analysis is missing.
[15]	Current developments and clinical applications of DL in medical image analysis	2022	Discuss DL models developed for various applications.	Focused on different application scenarios.	Requires improvement in the learning process.
[16]	A review of DL in medical image analysis	2022	DL models in big data.	Concentrated on different body areas.	Failed to address the dataset.
[17]	A review of DL-related techniques for medical image multi-organ segmentations	2021	Focus on pixel-wise classification.	Multi-organ image segmentation.	Failed to address computational constraints.

Authors in [26] investigated a weakly supervised, densely connected NN (wiseDNN) for brain disease diagnosis utilizing baseline MRI data and incomplete clinical scores. They specifically extracted multiscale image patches (positioned by anatomical landmarks) from MRI for capturing local-to-global structural data of imageries, and then developed weakly supervised densely connected networks for task-based extraction of joint prediction and imaging features of many clinical measures. Authors in [27] proposed the Iterative Sparse and DL (ISDL) method for joint deep extraction of features and difficult cortical region detection for diagnosing MCI and Alzheimer's Disease (AD). They, subsequently, examined sparse regression modules for finding critical cortical areas and integrated them into DFE modules to exclude irrelevant cortical areas from diagnosis.

In [28], an enhanced YOLOV5 method was explored for BT recognition related to MR imagery. In the meantime, it was observed that Hyperparameter Optimization (HPO) could be implemented through a Hybrid Grid Search Optimizer Algorithm (HGSOA) for enhancing the efficiency of cancer detection and tuning of hyperparameters in devised DNN. Authors in [29] examined an encoder-decoder network (ConvLSTM-Net) with a specific convolutional LSTM skip connection for deriving the spatiotemporal relationships of the nearby slices' attributes nonlinearly. It was found that mixed loss functions can be utilized to enhance the segmentation performance. Authors in [30] introduced a technique for filling missed data in longitudinal cohorts with anatomically possible imageries that captured subject-specific aging procedures. Initially, two new modules were presented within Synthmorph, a fast, existing DL-related diffeomorphic registration technique, for simulating the aging procedure among the last and first available MRI scans for all subjects in 3D. Table II exhibits the overview of the reviewed methods for brain-related diseases.

TABLE II. SUMMARY OF THE REVIEWED APPROACHES ON BRAIN-RELATED DISEASES

Ref.	Object	Modality	Model	Dataset	Metrics
[24]	Brain disease	MIT	RBM, DBN, SAE, DAE	Cerebral hemorrhage images	Relative reconstruction error
[25]	BT	MRI	DenseNet	Brain dataset with 3064 images	Accuracy, Precision, Recall, F1-score
[26]	Brain disease	MRI	Wise DNN	ADNI-1 and ADNI-2	MMSE, RMSE
[27]	AD.	MRI	IDSL	ADNI dataset	Accuracy, Sensitivity, Specificity, Time
[28]	BT	MRI	YOLOv5	BT-MRI	F1-score, Accuracy, MSE, PSNR, SSIM, FSIM, and CPU time
[29]	Brain penumbra	SPES image	ConvLSTM-Net	ISLES 2015	Dice score
[30]	AD	MRI	U-Net	ADNI and GENIC	SSIM, MAE, PSNR, DSC

B. Retinal Diseases

Authors in [31] proposed a robust method, called EfficientNet-B0 and EfficientDet-D0, for extracting key points for enriching the glaucoma detection efficiency while minimizing the execution time and model training. This method can precisely find the glaucomatous areas from the naked eye due to the robustness of the EfficientDet structure. It was noted that precise classification and recognition of glaucoma-affected imageries are required for managing the over-trained model datasets. Authors in [32] concentrated on a 4-class classification issue to mechanically identify DRUSEN, Choroidal Neovascularization (CNV), NORMAL, and Diabetic Macular Edema (DME) in Optical Coherence Tomography (OCT) imageries. The presented classifier method implemented an ensemble of 4 classifier method instances for finding retinal OCT imageries, each of which depended on an enhanced ResNet50. In [33], DeepSeeNet, a DL method, was formulated to categorize patients automatically. DeepSeeNet simulates the human grading procedure by identifying individual Applied Mechanics Division (AMD) risk components (pigmentary abnormality DRUSEN size) for all eyes and computing patient-related AMD severity scores utilizing the AREDS Simplified Severity Scale. Such outcomes emphasize the potential of DL for assisting and enhancing clinical decision-making in patients with AMD, such as initial AMD recognition and risk estimation to develop late AMD. Authors in [34] presented a diagnostic tool related to DL structure for a 4 -class classifier of ocular disease by automatic detection of CNV, DME, DRUSEN, and normal imageries in OCT scan of naked eye. The presented structure used OCT images and evaluated 3 CNN methods, nine, five, and seven layers, for detecting the several retinal layers, deriving valuable data, monitoring any novel deviations, and forecasting the many eye deformities. Authors in [35] designed a novel technique containing two major steps. The first included feature extraction, dataset preparation, and other related techniques to enhance the custom, DL-related, CenterNet method trained for classifying eye disease. At first, they generated annotations for suspected samples to locate the accurate Region of Interest (RoI), while the other part of the presented solution trained the CenterNet method over annotated imageries. In particular, DenseNet-100 was utilized as a feature extraction technique on which one-stage detectors, CenterNet, were employed for localizing and categorizing the disease lesions. In [36], pre-trained CNN methods, namely InceptionV3, VGG16, Xception, and DenseNet201, were utilized for classifying seven distinct retinal diseases from the dataset of images. Moreover, it has been found that Bayesian optimization can be implemented to select optimal hyperparameter values, and image augmentations can be utilized to increase the generalization abilities of the developed methods. Authors in [37] reported fundus image-related AI methods for differential analysis of retinal diseases. They categorized retinal imageries using 3 CNN methods, Inception v3, ResNet50, and VGG19. Additionally, a comparison to the efficiency of several dense FC layers was made. The prediction accuracy for diagnosing nine classes of 8 retinal diseases and normal control was approximately 87.42% in the ResNet50 method, including a dense layer having 128 nodes. Table III outlines the reviewed techniques on retinal-related diseases.

TABLE III. SUMMARY OF THE REVIEWED APPROACHES ON RETINAL-RELATED DISEASES

Ref.	Object	Modality	Model	Dataset	Metrics
[31]	Glaucoma	Fundus images	EfficientDet	ORIGA	Accuracy, mAP, IoU, Precision, Recall
[32]	Retinal diseases	OCT images	ResNet50	DHU dataset and UCSD dataset	Accuracy
[33]	Retinal diseases	OCT images	DeepSeeNet	AREDS dataset	ROC
[34]	Diagnosing DME, DRUSEN, CNV	OCT images	CNN	Independe nt dataset	Sensitivity, Specificity, Accuracy
[35]	Diabetic Eye Disease	Fundus images	DenseNet-100	EYEPACS and Diaretdb1	Accuracy, DSC
[36]	Retinal diseases	OCT images	Pretrained CNN models	Kaggle dataset	Accuracy, error
[37]	Retinal disease	Fundus images	ResNet50, VGG19, Inception v3	Independe nt dataset	Accuracy, Sensitivity, Specificity, PPV, NPV

C. Skin Related Diseases

Authors in [38] modeled an automatic melanoma classifier related to a Deep Convolutional Neural Networks (DCNNs) to categorize malignant versus benign melanoma precisely. The DCNN frameworks were prudently devised by organizing several layers that are accountable for uniquely extracting low to high-level skin image attributes. Other significant conditions in the DCNN model were selecting many filters and their sizes, optimizing hyperparameters, using suitable DL layers, and selecting the depth of the network. In [39], 4204 biopsy-proven images of melanoma and nevi (1:1) were utilized to train CNNs. Novel DL methods were compiled. For the experimentation, further 804 biopsy-proven dermoscopy imageries of nevi and melanoma (1:1) were arbitrarily offered to dermatologists of 9 German varsity clinics, who assessed the quality of all images and began the suggested treatment (a total of 19296 recommendations). Authors in [40] devised a computerized process of skin disease classification using DL-related MobileNetV2 and Long Short-Term Memory (LSTM). The MobileNet V2 method is fruitful with better accuracy and can operate on lightweight computational gadgets. The presented method was effective in preserving stateful data for accurate estimations. A grey-level co-occurrence matrix was utilized to evaluate the progress of diseased growth. Authors in [41] presented a technique to categorize melanoma imagery into benign and malignant classes by utilizing the DL method, and the T.L. MobileNetV2 network was utilized as the base method owing to its lightweight network structure. It was found that the presented technique is promising and can be applied further on mobile devices. In [42], a novel multiclass skin lesion classification technique utilizing optimal DL feature fusion and an ELM was devised. The proposed method includes the following primary steps: contrast enhancement and image acquisition, DL feature extraction deploying Transfer Learning (TL), optimal feature selection using a hybrid of the Entropy-Mutual Information (EMI) approach and whale optimization, the combination of selective features employing the modified canonical correlation-related technique, and ELM related classification. Authors in [43] presented a reliable method to diagnose skin cancer using dermoscopy images to enhance diagnostic abilities and healthcare experts' visual perception for discriminating malignant and benign lesions. Swarm Intelligence (SI) techniques were utilized for skin lesion RoI segmentation from dermoscopic imageries, and the Speeded-Up Robust Features (SURF) were deployed for extracting features of RoI marked as the optimal segmentation outcome, acquired through the Grasshopper Optimization Algorithm (GOA). Authors in [44] investigated 11 CNN single architecture configurations to compare their capability to categorize skin lesions properly. The optimal method concerning performance, number of parameters, and required memory size to be precisely determined was selected for the proposed mobile application to categorize skin lesions utilizing a common smartphone. Table IV showcases the summary of the reviewed approaches to skin-related diseases.

TABLE IV. OVERVIEW OF THE REVIEWED APPROACHES ON SKIN-RELATED DISEASES

Ref.	Object	Modality	Model	Dataset	Metrics
[38]	Melanoma	Dermoscopy	DCNN	ISIC	Accuracy, precision, recall, specificity, F1-score
[39]	Melanoma	Dermoscopy	DNN	ISIC	Sensitivity, Specificity, ROC
[40]	Skin diseases	Dermoscopy	LSTM, MobileNet	HAM10000	Sensitivity, Specificity, Accuracy, MCC
[41]	Melanoma	Dermoscopy	MobileNetV 2	ISIC, ISBI, MED-Node, PH2,	Accuracy
[42]	Skin cancer	Dermoscopy	ELM	HAM10000 and ISIC2018	Accuracy
[43]	Skin lesion	Dermoscopy	CNN, SURF	ISIC and PH2	Sensitivity, Specificity, Accuracy, MCC, F-measure, Precision, Dice coefficient
[44]	Skin lesion	Dermoscopy	11 CNN models	Ham10000	Accuracy, Precision, Recall, F1-Score

D. Respiratory Diseases

An overview of the methodologies applied to respiratory disease analysis is displayed in Table V. The goal of these studies was to classify abnormalities in respiratory cycles and detect diseases using respiratory sound recordings. Subsequently, a back-end DL network was employed to categorize spectrogram features into either diseases or different types of respiratory cycle anomalies.

TABLE V. SUMMARY OF REVIEWED APPROACHES ON RESPIRATORY-RELATED DISEASES

Ref.	Object	Modality	Model	Dataset	Metrics
[45]	Pediatric Pulmonary	CXR	Transfer learning	CXR dataset	Accuracy
[46]	lung cancer	CT images	LDA+ ML	Independent dataset	Accuracy, sensitivity, specificity
[47]	Lung disease	CXR	MARNet	CXR 14 dataset	Accuracy, precision, recall, F1-score
[48]	Pulmonary disease	CXR	MobileNetv2	Independent dataset	Accuracy, sensitivity, and specificity
[49]	COVID-19	X-rays	VGG16	COVID-19 dataset	Sensitivity, Specificity, F-Measure, Accuracy
[50]	Lung disease	spectrogram images	CNN	ICBHI 2017	Accuracy
[51]	Thoracic Syndrome	CXR	VGG19	NIH dataset	Precision, Recall, F1-score
[52]	Respiratory Anomalies and Lung Disease	spectrogram image	Teacher-Student scheme	ICBHI benchmark dataset	Accuracy

Authors in [45] presented a reliable, interpretable method for pediatric pulmonary health assessment, irrespective of the limited annotated pediatric CXR Image data sizes. This technique integrates CV tools and methods for reducing child mortality and morbidity using preventive and predictive medicine with reduced surveillance risks. Authors in [46] exhibited a precise prediction and classification of lung cancer utilizing technology that can be enabled by image processing and ML. The study employed 83 CT scans from 70 different patients as the dataset. It was observed that the geometric mean filter can be utilized at the time of picture pre-processing. As a result, image quality was enriched. The means approach was adopted to segment the imageries, with image parts being found through this segmentation. Afterwards, classifier techniques utilizing ML were deployed. K-Nearest Neighbours (KNN), Random Forest (RF), and Artificial Neural Networks (ANNs) were employed for the classification. Authors in [47] constructed MARnet, a Multiscale Adaptive Recurrent Neural Network (RNN), to find CXR images of lung-based diseases. Image features were extracted, and the authors cross-transferred the data derived from residual blocks and those derived from an adaptive structure to distinct layers, evading the reduction effects of residual structure on adaptive function. In [48], the issue of automated classification of pulmonary diseases, which includes recently appearing COVID-19, from X-ray images was considered. Mobile Net, was used and trained from scratch to investigate the importance of the derived features for classification.

Intending to offer a fully automatic and fast diagnosis, authors in [49] proposed the adoption of DL for COVID-19 recognition from X-rays. They introduced a technique with three stages: The first was to identify the presence of pneumonia in a CXR. The second one was to discern between pneumonia and COVID-19. The final step's aim was to localize zones in X-ray, symptomatic of COVID-19 presence. In [50], the deployed ICBHI 2017 database involves various background sounds, sample frequencies, and noise, which were utilized to classify lung sounds. The lung sound signals were primarily transformed into spectrogram images using the frequency technique. Two DL-related techniques were followed for classifying lung sounds. In the initial technique, a pre-trained CNN method was utilized for the SVM classifier, and feature extraction was utilized to classify the lung sounds. Authors in [51] used ML to identify several chest-related issues through CNN on an open dataset of CXRs. The technique has an edge over conventional image segmentation methods, including edge detection, thresholding, and k-means clustering. Finally, stochastic gradient descent was employed as an optimizer.

V. DISCUSSION AND CONCLUSION

The current review discusses the latest advanced Machine Learning (ML)-based biomedical image classification algorithms for various disorders [53-59]. The study seeks to help researchers and physicians in the biomedical imaging field to comprehend fundamental principles and contemporary Deep Learning (DL) models, examining contemporary biomedical image categorization methodologies devised for diverse disorders. A comprehensive comparative analysis of the examined methodologies is conducted to emphasize the distinctive features of the proposed technique, while Computer Vision (CV) and DL models are also investigated. This review enhances readers' understanding of potential future developments of DL models in biological image processing. DL has advanced in medical imaging diagnostics to improve the latter's efficacy. Nonetheless, the results of picture classification, segmentation, and registration limit their practical uses. DL has exhibited favorable results, including processing capability and improved accessibility to structured data. Nevertheless, the encountered obstacles are immediately surmounted prior to the execution of automated procedures. Utilizing innovative technology for role counting is practical, and many infrastructures are available to develop and evaluate DL approaches. DL is designed to address various issues in medical image diagnosis, including reduced accuracy of image classifiers, suboptimal picture enhancement, and diminished segmentation resolution. DL systems are assessed based on various data quantities to develop DL applications and infrastructure. These contribute to achieving success and optimal classifier accuracy, improving resolution through segmentation, and raising image quality by employing Convolutional Neural Networks (CNNs).

As DL technology is still in its initial stage, developing novel techniques with optimum accuracy can be feasible. In addition, enhancements in the analytic and modeling sub-domains are needed. With the purpose of utilizing CNNs to detect medicinal diseases, it is crucial to ensure that future analyses will continue to be on track, eventually enhancing the efficacy of disease detection approaches. The scale of the present medicinal image datasets is smaller. DL techniques require large datasets for training and their lack may cause overfitting problems. More novel techniques can be utilized to improve the accuracy and robustness of segmentation.

Detecting several diseases with Artificial Intelligence (AI) improves the knowledge of sustainable medical service, constituting an efficient tool for doctors. However, this remains an open challenge. It is assumed that the sequence of innovations and research outcomes will be achieved in the next several years.

ACKNOWLEDGMENT

This paper is derived from a research grant funded by the Research, Development, and Innovation Authority (RDIA) - Kingdom of Saudi Arabia - with grant number (13382-psu-2023-PSNU-R-3-1-EI-). The authors would like to acknowledge the support of Prince Sultan University, Riyadh, Saudi Arabia in paying the Article Processing Charges (APC) of this publication. This research is supported by Automated Systems and Soft Computing Lab (ASSCL), Prince Sultan University, Riyadh, Saudi Arabia. In addition, the authors wish to acknowledge the editor and anonymous reviewers for their insightful comments, which have improved the quality of this publication.

REFERENCES

[1] A. Ines, C. Dominguez, J. Heras, E. Mata, and V. Pascual, "Biomedical image classification made easier thanks to transfer and semi-supervised learning," *Computer Methods and Programs in Biomedicine*, vol. 198, Jan. 2021, Art. no. 105782, https://doi.org/10.1016/j.cmpb.2020.105782.

[2] C. Tchito Tchapga *et al.*, "Biomedical Image Classification in a Big Data Architecture Using Machine Learning Algorithms," *Journal of Healthcare Engineering*, vol. 2021, no. 1, 2021, Art. no. 9998819, https://doi.org/10.1155/2021/9998819.

[3] S. Pang, A. Du, M. A. Orgun, and Z. Yu, "A novel fused convolutional neural network for biomedical image classification," *Medical & Biological Engineering & Computing*, vol. 57, no. 1, pp. 107–121, Jan. 2019, https://doi.org/10.1007/s11517-018-1819-y.

[4] M. B. Assad and R. Kiczales, "Deep Biomedical Image Classification Using Diagonal Bilinear Interpolation and residual network," *International Journal of Intelligent Networks*, vol. 1, pp. 148–156, Jan. 2020, https://doi.org/10.1016/j.ijin.2020.11.001.

[5] A. Das, S. K. Mohapatra, and M. N. Mohanty, "Design of deep ensemble classifier with fuzzy decision method for biomedical image classification," *Applied Soft Computing*, vol. 115, Jan. 2022, Art. no. 108178, https://doi.org/10.1016/j.asoc.2021.108178.

[6] J. Yang *et al.*, "MedMNIST v2 -- A large-scale lightweight benchmark for 2D and 3D biomedical image classification," *arXiv e-prints*. Oct. 01, 2021, https://doi.org/10.48550/arXiv.2110.14795.

[7] S. Chakraborty and K. Mali, "An Overview of Biomedical Image Analysis From the Deep Learning Perspective," in *Research Anthology on Improving Medical Imaging Techniques for Analysis and Intervention*, Hershey, PA, USA: IGI Global, 2023, pp. 43–59.

[8] X. Gong, X. Xia, W. Zhu, B. Zhang, D. Doermann, and L. Zhuo, "Deformable Gabor Feature Networks for Biomedical Image Classification," in *IEEE/CVF Winter Conference on Applications of Computer Vision*, Waikoloa, HI, USA, Jan. 2021, pp. 4004–4012.

[9] H. Seo *et al.*, "Machine learning techniques for biomedical image segmentation: An overview of technical aspects and introduction to state-of-art applications," *Medical Physics*, vol. 47, no. 5, pp. e148–e167, 2020, https://doi.org/10.1002/mp.13649.

[10] H. Barzekar and Z. Yu, "C-Net: A reliable convolutional neural network for biomedical image classification," *Expert Systems with Applications*, vol. 187, Jan. 2022, Art. no. 116003, https://doi.org/10.1016/j.eswa.2021.116003.

[11] M. A. Abdou, "Literature review: efficient deep neural networks techniques for medical image analysis," *Neural Computing and Applications*, vol. 34, no. 8, pp. 5791–5812, Apr. 2022, https://doi.org/10.1007/s00521-022-06960-9.

[12] T. Zhou, S. Ruan, and S. Canu, "A review: Deep learning for medical image segmentation using multi-modality fusion," *Array*, vol. 3–4, Sep. 2019, Art. no. 100004, https://doi.org/10.1016/j.array.2019.100004.

[13] D. R. Sarvamangala and R. V. Kulkarni, "Convolutional neural networks in medical image understanding: a survey," *Evolutionary Intelligence*, vol. 15, no. 1, pp. 1–22, Mar. 2022, https://doi.org/10.1007/s12065-020-00540-3.

[14] I. Rizwan I Haque and J. Neubert, "Deep learning approaches to biomedical image segmentation," *Informatics in Medicine Unlocked*, vol. 18, Jan. 2020, Art. no. 100297, https://doi.org/10.1016/j.imu.2020.100297.

[15] X. Chen *et al.*, "Recent advances and clinical applications of deep learning in medical image analysis," *Medical Image Analysis*, vol. 79, Jul. 2022, Art. no. 102444, https://doi.org/10.1016/j.media.2022.102444.

[16] S. Suganyadevi, V. Seethalakshmi, and K. Balasamy, "A review on deep learning in medical image analysis," *International Journal of Multimedia Information Retrieval*, vol. 11, no. 1, pp. 19–38, Mar. 2022, https://doi.org/10.1007/s13735-021-00218-1.

[17] Y. Fu, Y. Lei, T. Wang, W. J. Curran, T. Liu, and X. Yang, "A review of deep learning based methods for medical image multi-organ segmentation," *Physica Medica*, vol. 85, pp. 107–122, May 2021, https://doi.org/10.1016/j.ejmp.2021.05.003.

[18] G. Litjens *et al.*, "A survey on deep learning in medical image analysis," *Medical Image Analysis*, vol. 42, pp. 60–88, Dec. 2017, https://doi.org/10.1016/j.media.2017.07.005.

[19] S. Benjamens, P. Dhunnoo, and B. Meskó, "The state of artificial intelligence-based FDA-approved medical devices and algorithms: an online database," *npj Digital Medicine*, vol. 3, no. 1, pp. 1–8, Sep. 2020, https://doi.org/10.1038/s41746-020-00324-0.

[20] E. Beede *et al.*, "A Human-Centered Evaluation of a Deep Learning System Deployed in Clinics for the Detection of Diabetic Retinopathy," in *CHI Conference on Human Factors in Computing Systems*, Honolulu, HI, USA, Apr. 2020, pp. 1–12, https://doi.org/10.1145/3313831.3376718.

[21] M. G. Crowson *et al.*, "A contemporary review of machine learning in otolaryngology–head and neck surgery," *The Laryngoscope*, vol. 130, no. 1, pp. 45–51, 2020, https://doi.org/10.1002/lary.27850.

[22] T. Hirasawa *et al.*, "Application of artificial intelligence using a convolutional neural network for detecting gastric cancer in endoscopic images," *Gastric Cancer*, vol. 21, no. 4, pp. 653–660, Jul. 2018, https://doi.org/10.1007/s10120-018-0793-2.

[23] A. D. Weston *et al.*, "Automated Abdominal Segmentation of CT Scans for Body Composition Analysis Using Deep Learning," *Radiology*, vol. 290, no. 3, pp. 669–679, Mar. 2019, https://doi.org/10.1148/radiol.2018181432.

[24] R. Chen, J. Huang, Y. Song, B. Li, J. Wang, and H. Wang, "Deep learning algorithms for brain disease detection with magnetic induction tomography," *Medical Physics*, vol. 48, no. 2, pp. 745–759, 2021, https://doi.org/10.1002/mp.14558.

[25] N. Noreen, S. Palaniappan, A. Qayyum, I. Ahmad, M. Imran, and M. Shoaib, "A Deep Learning Model Based on Concatenation Approach for the Diagnosis of Brain Tumor," *IEEE Access*, vol. 8, pp. 55135–55144, Jan. 2020, https://doi.org/10.1109/ACCESS.2020.2978629.

[26] M. Liu, J. Zhang, C. Lian, and D. Shen, "Weakly Supervised Deep Learning for Brain Disease Prognosis Using MRI and Incomplete Clinical Scores," *IEEE Transactions on Cybernetics*, vol. 50, no. 7, pp. 3381–3392, Jul. 2020, https://doi.org/10.1109/TCYB.2019.2904186.

[27] Y. Chen and Y. Xia, "Iterative sparse and deep learning for accurate diagnosis of Alzheimer's disease," *Pattern Recognition*, vol. 116, Aug. 2021, Art. no. 107944, https://doi.org/10.1016/j.patcog.2021.107944.

[28] S. Arunachalam and G. Sethumathavan, "An effective tumor detection in MR brain images based on deep CNN approach: i- YOLOV5," *Applied Artificial Intelligence*, vol. 36, no. 1, Dec. 2022, Art. no. e2151180, https://doi.org/10.1080/08839514.2022.2151180.

[29] L. Liu, P. Zhang, G. Liang, S. Xiong, J. Wang, and G. Zheng, "A spatiotemporal correlation deep learning network for brain penumbra disease," *Neurocomputing*, vol. 520, pp. 274–283, Feb. 2023, https://doi.org/10.1016/j.neucom.2022.11.041.

[30] J. Fu *et al.*, "Fast three-dimensional image generation for healthy brain aging using diffeomorphic registration," *Human Brain Mapping*, vol. 44, no. 4, pp. 1289–1308, 2023, https://doi.org/10.1002/hbm.26165.

[31] M. Nawaz *et al.*, "An Efficient Deep Learning Approach to Automatic Glaucoma Detection Using Optic Disc and Optic Cup Localization," *Sensors*, vol. 22, no. 2, Jan. 2022, Art. no. 434, https://doi.org/10.3390/s22020434.

[32] F. Li *et al.*, "Deep learning-based automated detection of retinal diseases using optical coherence tomography images," *Biomedical Optics Express*, vol. 10, no. 12, pp. 6204–6226, Nov. 2019, https://doi.org/10.1364/BOE.10.006204.

[33] Y. Peng *et al.*, "DeepSeeNet: A Deep Learning Model for Automated Classification of Patient-based Age-related Macular Degeneration Severity from Color Fundus Photographs," *Ophthalmology*, vol. 126, no. 4, pp. 565–575, Apr. 2019, https://doi.org/10.1016/j.ophtha.2018.11.015.

[34] A. Tayal, J. Gupta, A. Solanki, K. Bisht, A. Nayyar, and M. Masud, "DL-CNN-based approach with image processing techniques for diagnosis of retinal diseases," *Multimedia Systems*, vol. 28, no. 4, pp. 1417–1438, Aug. 2022, https://doi.org/10.1007/s00530-021-00769-7.

[35] T. Nazir *et al.*, "Detection of Diabetic Eye Disease from Retinal Images Using a Deep Learning Based CenterNet Model," *Sensors*, vol. 21, no. 16, Jan. 2021, Art. no. 5283, https://doi.org/10.3390/s21165283.

[36] M. Subramanian *et al.*, "Diagnosis of Retinal Diseases Based on Bayesian Optimization Deep Learning Network Using Optical Coherence Tomography Images," *Computational Intelligence and Neuroscience*, vol. 2022, no. 1, Jan. 2022, Art. no. 8014979, https://doi.org/10.1155/2022/8014979.

[37] K. M. Kim *et al.*, "Development of a Fundus Image-Based Deep Learning Diagnostic Tool for Various Retinal Diseases," *Journal of Personalized Medicine*, vol. 11, no. 5, May 2021, Art. no. 321, https://doi.org/10.3390/jpm11050321.

[38] R. Kaur, H. GholamHosseini, R. Sinha, and M. Linden, "Melanoma Classification Using a Novel Deep Convolutional Neural Network with Dermoscopic Images," *Sensors*, vol. 22, no. 3, Jan. 2022, Art. no. 1134, https://doi.org/10.3390/s22031134.

[39] T. J. Brinker *et al.*, "Deep neural networks are superior to dermatologists in melanoma image classification," *European Journal of Cancer*, vol. 119, pp. 11–17, Sep. 2019, https://doi.org/10.1016/j.ejca.2019.05.023.

[40] P. N. Srinivasu, J. G. SivaSai, M. F. Ijaz, A. K. Bhoi, W. Kim, and J. J. Kang, "Classification of Skin Disease Using Deep Learning Neural Networks with MobileNet V2 and LSTM," *Sensors*, vol. 21, no. 8, Jan. 2021, Art. no. 2852, https://doi.org/10.3390/s21082852.

[41] R. Indraswari, R. Rokhana, and W. Herulambang, "Melanoma image classification based on MobileNetV2 network," *Procedia Computer Science*, vol. 197, pp. 198–207, Jan. 2022, https://doi.org/10.1016/j.procs.2021.12.132.

[42] F. Afza, M. Sharif, M. A. Khan, U. Tariq, H.-S. Yong, and J. Cha, "Multiclass Skin Lesion Classification Using Hybrid Deep Features Selection and Extreme Learning Machine," *Sensors*, vol. 22, no. 3, Jan. 2022, Art. no. 799, https://doi.org/10.3390/s22030799.

[43] P. Thapar, M. Rakhra, G. Cazzato, and M. S. Hossain, "A Novel Hybrid Deep Learning Approach for Skin Lesion Segmentation and Classification," *Journal of Healthcare Engineering*, vol. 2022, no. 1, 2022, Art. no. 1709842, https://doi.org/10.1155/2022/1709842.

[44] I. Kousis, I. Perikos, I. Hatzilygeroudis, and M. Virvou, "Deep Learning Methods for Accurate Skin Cancer Recognition and Mobile Application," *Electronics*, vol. 11, no. 9, Jan. 2022, Art. no. 1294, https://doi.org/10.3390/electronics11091294.

[45] G. Marvin and Md. G. R. Alam, "Explainable Augmented Intelligence and Deep Transfer Learning for Pediatric Pulmonary Health Evaluation," in *International Conference on Innovations in Science, Engineering and Technology*, Chittagong, Bangladesh, Feb. 2022, pp. 272–277, https://doi.org/10.1109/ICISET54810.2022.9775845.

[46] S. Nageswaran *et al.*, "Lung Cancer Classification and Prediction Using Machine Learning and Image Processing," *BioMed Research International*, vol. 2022, Aug. 2022, Art. no. 1755460, https://doi.org/10.1155/2022/1755460.

[47] B. Wang and W. Zhang, "MARnet: multi-scale adaptive residual neural network for chest X-ray images recognition of lung diseases," *Mathematical Biosciences and Engineering*, vol. 19, no. 1, pp. 331–350, Jan. 2022, https://doi.org/10.3934/mbe.2022017.

[48] I. D. Apostolopoulos, S. I. Aznaouridis, and M. A. Tzani, "Extracting Possibly Representative COVID-19 Biomarkers from X-ray Images with Deep Learning Approach and Image Data Related to Pulmonary Diseases," *Journal of Medical and Biological Engineering*, vol. 40, no. 3, pp. 462–469, Jun. 2020, https://doi.org/10.1007/s40846-020-00529-4.

[49] L. Brunese, F. Mercaldo, A. Reginelli, and A. Santone, "Explainable Deep Learning for Pulmonary Disease and Coronavirus COVID-19 Detection from X-rays," *Computer Methods and Programs in Biomedicine*, vol. 196, Nov. 2020, Art. no. 105608, https://doi.org/10.1016/j.cmpb.2020.105608.

[50] F. Demir, A. Sengur, and V. Bajaj, "Convolutional neural networks based efficient approach for classification of lung diseases," *Health Information Science and Systems*, vol. 8, no. 1, Dec. 2019, Art. no. 4, https://doi.org/10.1007/s13755-019-0091-3.

[51] S. Juneja, A. Juneja, G. Dhiman, S. Behl, and S. Kautish, "An Approach for Thoracic Syndrome Classification with Convolutional Neural Networks," *Computational and Mathematical Methods in Medicine*, vol. 2021, no. 1, Jan. 2021, Art. no. 3900254, https://doi.org/10.1155/2021/3900254.

[52] L. Pham, H. Phan, R. Palaniappan, A. Mertins, and I. McLoughlin, "CNN-MoE Based Framework for Classification of Respiratory Anomalies and Lung Disease Detection," *IEEE Journal of Biomedical and Health Informatics*, vol. 25, no. 8, pp. 2938–2947, Dec. 2021, https://doi.org/10.1109/JBHI.2021.3064237.

[53] P. K. N. Banu, A. T. Azar, and H. H. Inbarani, "Fuzzy firefly clustering for tumour and cancer analysis," *International Journal of Modelling, Identification and Control*, vol. 27, no. 2, pp. 92–103, Jan. 2017, https://doi.org/10.1504/IJMIC.2017.082941.

[54] J. Amin, M. Sharif, M. Yasmin, T. Saba, M. A. Anjum, and S. L. Fernandes, "A New Approach for Brain Tumor Segmentation and Classification Based on Score Level Fusion Using Transfer Learning," *Journal of Medical Systems*, vol. 43, no. 11, Oct. 2019, Art. no. 326, https://doi.org/10.1007/s10916-019-1453-8.

[55] H. Inbarani H., A. T. Azar, and J. G, "Leukemia Image Segmentation Using a Hybrid Histogram-Based Soft Covering Rough K-Means Clustering Algorithm," *Electronics*, vol. 9, no. 1, Jan. 2020, Art. no. 188, https://doi.org/10.3390/electronics9010188.

[56] T. Mahmood, A. Rehman, T. Saba, L. Nadeem, and S. A. O. Bahaj, "Recent Advancements and Future Prospects in Active Deep Learning for Medical Image Segmentation and Classification," *IEEE Access*, vol. 11, pp. 113623–113652, Jan. 2023, https://doi.org/10.1109/ACCESS.2023.3313977.

[57] E. Emary, H. M. Zawbaa, A. E. Hassanien, G. Schaefer, and A. T. Azar, "Retinal blood vessel segmentation using bee colony optimisation and pattern search," in *International Joint Conference on Neural Networks*, Beijing, China, Jul. 2014, pp. 1001–1006, https://doi.org/10.1109/IJCNN.2014.6889856.

[58] A. Koubaa, A. Ammar, M. Alahdab, A. Kanhouch, and A. T. Azar, "DeepBrain: Experimental Evaluation of Cloud-Based Computation Offloading and Edge Computing in the Internet-of-Drones for Deep Learning Applications," *Sensors*, vol. 20, no. 18, Jan. 2020, Art. no. 5240, https://doi.org/10.3390/s20185240.

[59] T. Saba, A. Sameh, F. Khan, S. A. Shad, and M. Sharif, "Lung Nodule Detection based on Ensemble of Hand Crafted and Deep Features," *Journal of Medical Systems*, vol. 43, no. 12, Nov. 2019, Art. no. 332, https://doi.org/10.1007/s10916-019-1455-6.