Computational Framework for Automated Disease Prediction Using Radiological Scans

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Abstract
Automated disease prediction from radiological scan is one of the hot and promising research areas of AI for reliable and fast clinical diagnosis. In this paper, an efficient deep learning based automated computational framework is proposed for disease prediction using Computed Tomography, Magnetic Resonance Imaging and X-ray images. The proposed computational framework introduces various image processing techniques like resizing, normalization and data augmentation to enhance the quality of image and provides a standarized input for deep learning models training. Convolutional Neural Networkhas been utilized in the proposed computational framework to automatically detect several local features from radiological images and classify them into disease and healthy classes without handcrafted feature extraction step. The framework has been trained and tested on open source medical image benchmark datasets and the classification outcomes have been evaluated using several metrics such as accuracy, precision, recall, F1-score, etc. The results obtained from proposed system showed its reliable classification performance, while provides quick diagnosis, and gave a clinical decision support system. The proposed system not only infers a good computer-aided diagnosis system but also established a good platform for further research using transfer learning, explainable AI and multi-class disease prediction.

Keywords: Radiological Image Analysis, Deep Learning, Convolutional Neural Network, Medical Image Classification, Disease Prediction, Computer-Aided Diagnosis.

INTRODUCTION

Medical imaging has become an integral part of modern medicine with radiological studies (namely CT, MRI and plain X-ray images) used daily in the diagnosis of diseases and their application gaining access to normally difficult or impossible to examine parts of the body. Hence there is a significant volume of radiological images which need to be read and understood by radiologists efficiently everyday.In last decades, progressive advances in AI especially in Deep learning has been observed over this period[1]. And in recent ten years, several groundbreaking advancements, new techniques of art have been made in the research of medical image analysis including; automatic systems that are employ able to both detect the image biomarkers and the robust categorization of the disease processes.

CNNs which is a DL structure has been found to perform reliably over several other techniques to the recognition of complex spatial features from raw image data without necessity of any manual feature extraction[2]. Of hierarchies have contributed to numerous advancements in computer aid diagnosis in modalities.This is a Deep learning enabled Fully automatic computerized disease prediction system with CT, MRI and X-ray images. This system uses image processing techniques, i.e. Resizing, normalization, and data augmentation as input image processing step; along with CNN based classifier to compute diseased image prediction. The main aim of this system are to optimize the prediction accuracy, prediction time and to build decision support system for clinician. As the power of this system is scalable and hybrid, i.e. extendable to use more sophisticated deep learning algorithms, transfer learning, and this explainable AI framework[3]. It would be a boost for intelligent computer aided disease prediction system with less time, wide objective decision and dependability.

RECENT ADVANCES IN DEEP LEARNING-BASED RADIOLOGICAL IMAGE ANALYSIS FOR AUTOMATED DISEASE PREDICTIONS

Recent progress of deep learning has been contribute to the success of radiological image analysis. High performance intelligent systems based on deep learning for disease detection and diagnosis have been established successfully. The radiological images taken from different imaging modalities, and x-ray. Storage provide enormous visual information which needs radiologists to read and diagnose efficiently and accurately. It takes too much time which is reinforced by deep learning method in recent years[4].

Another factor that might have contributed to the convenience of use and the high efficiency of CNNs is their ability to automatic learn high or even deep features from raw data, which is so undoubtedly contrasted to the classical pattern recognition algorithms used in general computer-aided diagnosis, in which features are designed and hand-crafted by people. On top of that, transfer learning was successfully implemented on various architectures of ResNet, DenseNet, EfficientNet, and ViTs to reach promising performance of classification with greatly reduced training times[5].

Recently, works are being to unifys attention mechanism, the problem of multimodal learning, and some of the already studied XAI methods, so to further promote the diagnostic performance and model interpretability. For example, by providing visual explanations such as Gradient-weighted Class Activation Map visualization, clinicians can understand the prediction reason of the automated diagnostic system, which would bring the progress of trust into the future application[6]. Also, the application of utilizing the full cloud based computing combined with GPU acceleration, in turn, take new instant wise radiological image analysis applications into clinical decision making on high- resolution images, as well as help improve the diagnostic quality of care, which is indeed promising in the 21 st century visual health care.

Table 1: Comparative Analysis of State-of-the-Art Medical Image Classification Methods

Reference	Method	Dataset/Application	Advantages	Limitations
Study 1	CNN-based classification	X-ray disease detection	Automat feature extraction	Requires large training data
Study 2	Transfer Learning (ResNet/DenseNet)	CT and MRI classification	Improve d accuracy with limited data	Domain adaptation issues
Study 3	Vision Transformer (ViT)	Medical image analysis	Captures global image relations hips	High computation al cost
Study 4	CNN + Transformer Hybrid	Radiological image classification	Combin es local and global features	Complex architecture
Study 5	Explainable AI-based Models	Clinical decision support	Provides redictio n visualiza tion	Additional processing overhead

Proposed Intelligent Framework for Automated Disease Prediction Using Radiological Scans

This proposed deep learning-enabled computational framework aims to deploy an intelligent and efficient automated disease predication system over the medical images obtained via Computed Tomography, Magnetic resonance imaging, and X-ray imaging technologies. This deep learning-enabled framework integrates advanced image pre-processing, feature extraction, image classification with deep learning approach, and disease predication modules into a one pipeline to better diagnose different diseases with a significantly less human expertise consumed in the manual feature engineering. The framework takes advantage of CNN that have high efficiency in rapidly learning discriminative information to identify various complex diseases and effects without requiring any domain-specific expert knowledge in feature engineering[7].

Initially, radiological images were obtained from accessible sources of medical imaging information which was used to house normal and abnormal radiological images[9]. The images obtained from sources had different sizes, resolutions, brightness and contrast depending on the type of radiological modality and hospital, thus, the images were pre-processed to normalize all images to be at the same standard. Standard level images were normalized in terms of resizing, grayscaling and augmentation. These processe increased the image quality, minimized the noise and also minimized the overfitting problem.

The image, once processed, then is passed into the feature extraction side of the system which is a CNN. The CNN has a number of convolutional layers which have the power to learn features of the image at all levels of abstraction ranging from the lowest levels of textures and edges to the highest levels of anatomy and structure of the pathology[8]. Re Lu activation functions are then learned after each convolution to make the model more non-linear. Max-pooling layers are used to reduce the size of the image and discard unwanted information.

The feature maps from the model is then flattened to a 1-dimensional feature vector and passes through the final dense layers to classify disease. It uses the feature vector extracted and with the help of it, Softmax layer finds the most likely class from its output classes and classify the input image as a class with disease or normal class with highest confidence score. To provide faster convergence and more efficient classification Adam optimizer with a categorical cross-entropy loss function is used in training the model.

To conclude, the final successful designed prediction framework also presents a scalable, robust and time saving computer aided diagnosis system to well help the clinicians for applying early detection of diseases and clinical decision making[10]. Moreover, the framework can be further enhanced with the transfer learning paradigm, attention mechanism, XAI, multi-class disease classification in order to optimize the prediction accuracy, model explainability and clinical practicality.

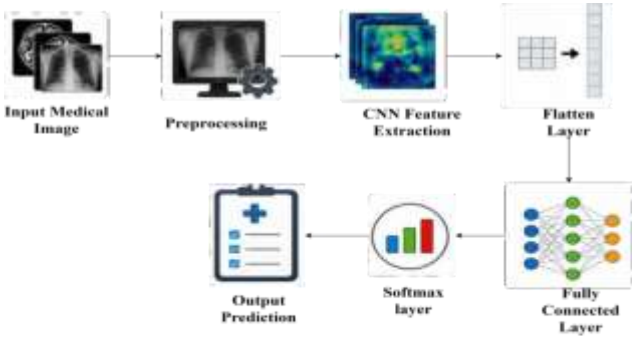

Figure 1: System Architecture

The system begins its work by gathering patient data from medical records and information collected through wearable devices. The data first undergoes preprocessing before secure transmission to the cloud system. Researchers utilize the cloud environment as a data storage solution to perform their artificial intelligence algorithm analysis. The system detects abnormal data patterns while it forecasts potential health threats which it shows to users through mobile applications and dashboard displays.

A. Advantages of the Proposed Computational Framework

Based on deep learning, computer-aided disease prediction system provide many benefits of using radiological images for automated disease prediction. The deep learning CNNs based framework is able to extract the features from CT, MRI, X-ray images automatically, efficiently, without led by humans, so ground-truth labels is required but not handmade features, and reaches more robust diagnosis result[11]. Pre-possessing step, the so-called resizing, normalization, data augmentation etc., optimize the image quality, reduce noise and boosts the training data set, thus to have higher generalization ability of deep learning models. The system can provide health practitioners a quick and reliable prediction system in the way similar with how human doctors studied the medical images, so to accelerate the speed of diagnosis compare with traditional doctor doctor diagnosis approach based on clinical skills and analysis; It also has the advantage of high efficiency for computing large amount of the medical image data set; Modularity design enable it invocation of advanced deep learning techniques such as transfer learning, self- attention mechanism, and XAI model to dramatically augment the prediction efficiency; It is also scalable, extendable to multi-category disease prediction system, and extensible with multi-modality images without much modification. Its cost for time and labor is few, can mitigate the human errors in using radiological images, improve the efficiency and accuracy of diagnosis system, provide good support to health practitioners and benefit common people[13]. Overall, this deep learning based computer-aided disease prediction system is robust, expandable, and intelligent to combine computer-aided medical image analysis and deep learning techniques to meet the increasing demand of faster, specific disease prediction system.

I. Systematic Approach for Automated Disease Prediction Using Radiological Scans

The designed systematic workflow has created an excellent pipeline for disease prediction automatically using radiological images. The framework takes in image loading, preprocessing, deep features extraction, disease recognition and performance evaluation step by step. With the systematic workflow designed, the framework could be applied to deal with different images and deliver the correct prediction results to the clinician in time[12].

a. Radiological Image Acquisition

At the initial stage of the proposed system, the radiological images are acquired from wide range publicly available datasets of medical images (including Computed Tomography, Magnetic Resonance Image, X-ray image, etc).and comprise both healthy and sick samples for supervised learning[15]. The images are categorized into relevant class, so label of image is assigned as per image class. Since the images are obtained from various hospitals having different number of computers and cameras, the image resolution, intensity, and structure varies for each. Large amount of data gives deep learning system enough data to generalize the disease property efficiently.

b. Image Preprocessing

Image preprocessings is one of the step in our pipeline process. Enhance image quality and regulazation of dataset of images was performed before input into deep learning model. Every radiological images was rezise to the fixed size resolution. Pixel intensity normalisation was adopted to ensure the numerical stability of training process and fasten the training speed. Image was convert Grayscale mode if it did not limit image defiinition. Removal of noise and Sharpen occurs no to make differences, but it can be used to emphasize on main image features[16]. Hence, data augmentation with image rotation, horizontal translation, horizontal flip, zoom and scale have been used in order to regulazation of dataset because of limited number of dataset. However, these process can help to minimize the part of variation which caused by different imaging device and circumstances of image acquisition.

c. Deep Feature Extraction Using CNN

Once preprocessed, the standardized images can then be inputted into the CNN for unsupervised feature learning[14]. The CNN architecture has several convolutional layers which learn the image at increasing levels of abstraction from textures and edges to anatomical and pathological structures. The series of convolutional layers, each followed by a Rectified Linear Unit activation, provides the power to discover non-linear relations among subtle disease features. The following max pooling layers then 'subsample' the feature map, achieve translation invariance, and minimize the computational load. Unlike traditional machine learning techniques in which features must be explicitly designed, the CNN ‘learns’ a highly descriptive feature model from the image.

Table 2: Training Configuration

Parameter	Value
Optimizer	Adam
Learning Rate	0.001
Batch Size	32
Number of Epochs	50
Loss Function	Categorical Cross-Entropy
Image Size	224 × 224
Input Channel	1 (Grayscale)

***d.* Disease Classification**

The feature map from the previous layer is flattened and fed to the one dimensional feature vector. The feature vector is then passed to the fully connected dense layers which determine the class of the disease in a radiological image. Dense layers are used to model the relationship between the extracted features of the image and the potential categories of the disease so that the relationships can be learned by the Dense layers to adjust the weights and learn the image disease relationship using the activation functions. Fully connected layer uses the softmax activation function in the output layer which maximizes the probability of all the classes and predicts that whether the given radiological image is a normal or diseased image. Adam algorithm optimization is used to speed up the convergence rate of the classification, and the learning is improved using the cross-entropy loss function.

***e.* Performance Evaluation and Prognostics.**

The final aspect of the framework involved the evaluation of the trained model and classification of previously unseen radiological images. The data is partitioned into training data and testing data so that the ability of the trained model to generalize to new, previously unseen data can be assessed. Classification performance will be assessed using accuracy, precision, recall, F1-score and the analysis of the confusion matrix. If evaluation indicates the trained model is valid and is robust, then it will be used to give disease predictions for unseen CT, MRI or X-ray images in real-time[17]. The automated prediction of diseases will help free up more time for healthcare practitioners to think about each patient personally, rather than dedicating large amounts of time to diagnosing the patient. Small improvements which can be made to the trained model in order to optimize it ready for deployment in a clinical setting will be identified during this stage of the framework so that the framework is easily scalable, reliable and applicable in a realistic clinical setting.
where:
I = Input image
K = Convolution kernel F = Output feature map

b. Rectified Linear Unit (ReLU) Activation Function

By incorporating the ReLu activation into the architecture, the neural network can learn more difficult associations learned from radiology images. The activation function during the feature extraction phase sets the negative activation to zero and preserves the positive values thereby reduces the timememory-computation required by the neural network and prevent gradient saturation[22]. The time-savings provided by the activation function accelerates the convergence of the model and allows the neural network to learn more informative disease representation. The removal of unnecessary negative responses improves feature discrimination and disease specific features such as abnormality of the anatomy can possibly emerge. ReLu is cheap to perform and not surprisingly, is one of the most favored activation functions for deep neural networks for medical images.

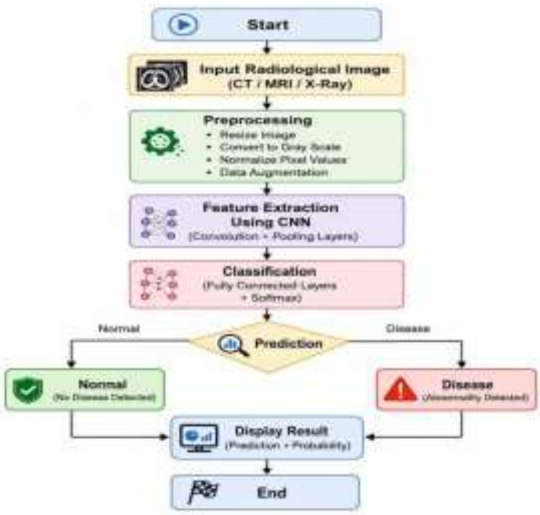

Fig 2: Flowchart

HIERARCHICAL DEEP REPRESENTATION LEARNING AND COMPUTATIONAL INTELLIGENCE FRAMEWORK FOR AUTOMATED RADIOLOGICAL DISEASE PREDICTION

The suggested deep learning based computational intelligence framework employs a set of established deep learning algorithms to predict the disease from radiological images accurately and reliably[18]. All algorithms are dedicated to a different task: image preprocessing, extraction of hierarchical features, non-linearity, spatial dimensionality reduction, optimization and final prediction. The interplay of all these algorithms enables this framework to discover the classifiable representations of the images to improve the prediction accuracy, computational efficiency and generalizability.

a. Convolutional Neural Network (CNN) for Hierarchical Feature Extraction

The CNN is the architecture for the automatic feature extractor in our proposed model. With the use of multiple convolutional filters CNN inductively learns to extract image features from low levelnto high level from radiological images without any domain knowledge in feature engineering, unlike traditional machine learning paradigm[20]. The feature maps generated from CNN preserve the rich spatial structure of input images as well as the pattern that characterizes different pathologies for disease classification. The CNN stacks many filters to successfully extract high level features.

$\boldsymbol{f(x)} = \mathbf{max(0, x)(2)}$

c. **Max-Pooling Algorithm for Spatial Feature Reduction**

Max-pooling. Max-pooling is used for the size reduction of the feature maps within the CNN. Max-pooling (an operation where the maximum of the values within a feature maps' local pooling window is calculated) removes any duplicated data within the feature maps, therefore speeding up the training time, with only a small loss of information. Max-pooling also increases the translation invariance of the CNN, therefore the prediction will be less sensitive to small variations in the position and orientation of the radiological images[19]. The size of each feature map is progressively reduced by max-pooling. This size reduction of the features learned by a CNN, therefore reduces the number of parameters to learn from, and so CNNs can be trained more quickly without a large reduction in the range of information that can be used to predict disease from radiological scans.

$\boldsymbol{P(i, j) = max\ F(m.n)(3)}$

d. **Adam Optimization Algorithm**

Adam optimization is the most suitable optimization method for training the depicted CNN as it provides fast convergence to train a network in comparison to other optimization algorithms. This optimization algorithm updates the network parameters more efficiently by means of multiple adaptive learning rates. Adam is involved with an adaptive learning rate for the training network parameters as well as with the velocity correction, which suppresses the oscillations providing a minimum perplexity while minimizing the loss function. In [15], it has been demonstrated that the training of CNN with Adam optimizer converges to the optimal parameters faster than other adaptive algorithms.

$\mathbf{m_t\theta} = \boldsymbol{\theta} - \propto \quad \_ \quad \mathbf{(4)}$

$\mathbf{F(i, j)} = \sum \sum \boldsymbol{I(i + m, j + n) * K(m, n)\ (1)}$

$\mathbf{t{+}1t}$

$\sqrt{\mathbf{v_t}} + \varepsilon$

$\boldsymbol{m \quad n}$

The fully connected single output will then be passed to Softmaxalgorithm , with it. So the classification of radiological image is judged, when the output yields to stable value tell us that results the normalized probability of falling into each class of disease[21]. The normal and abnormal probability of each disease of the input radiological images is normalized as the output of the softmax algorithm. We will select the class label as the class whose normalized probability value is maximum. The prediction will be more stable by this algorithm, and the results will be able to distinguish normal radiological images with abnormal images and it can diagnose in our computer aided diagnosis system as well. hence establishing the robustness of the suggested deep learning based solution.

$$\boldsymbol{P(y\ )} = \frac{\boldsymbol{e^{z_i}}}{\Sigma} \qquad \mathbf{(4)}$$

where:

$\boldsymbol{i \quad c}$

$\boldsymbol{z{=}1}$

$\boldsymbol{e^{zj}}$

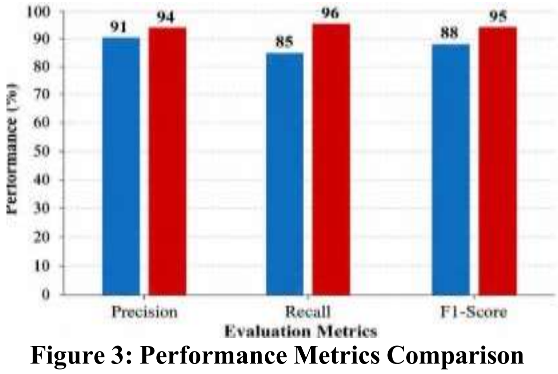

Figure 3: Performance Metrics Comparison

z_i= Output score of class i C = Total number of classes P(yi) = Probability of class i

II. RESULTS AND FINDINGS

The proposed deep learning based computational framework was evaluated with current available performance evaluation metrics to verify the feasibility of automatic disease prediction from radiological images. The experimental results were evaluated by confusion matrix, training-and-validation-accuracy plot, and training-and-validation-loss plot[24]. All the performance evaluation metrics, including confusion matrix, accuracy plot, and loss plot, gave full idea on the classification ability, learning tendency, convergence speed and generalization ability of the proposed CNN. The confusion matrix reflected the number of correctly/incorrectly classified samples, and the accuracy plot as well as the loss plot reflected the learning tendency of the proposed CNN in the sequential training iterations. According to the above experimental analysis, the deep learning based computational framework was proved feasible and reliable in classifying the normal and diseased radiological images in robust, reliable and stable manner, which might further prove beneficial for real-world computer-aided intelligent diseased diagnosis system in practical clinical system.

Table 3: Performance Metrics of the Proposed CNN Model

Class	Precision	Recall	F1-Score
Normal	0.91	0.85	0.88
Disease	0.94	0.96	0.95
Weighted Average	0.93	0.93	0.93

The state of the art classification performance predicted by the suggested CNN model, , in terms of precision, recall and F1-score is depicted in table 3.From the table 3, it was seen that the disease class had the highest values of precision and recall thus classifying the radiological disease images accurately with less false predictions even the normal class had an overall good classification as well. In total , the weighted average F1-score of 93% was reached thus confirming the ever lasting prediction of the model, and The figure 3 shows the comparison of the precision, recall and F1-score of the proposed CNN for normal, disease class. The disease class score in each system output value indicates the better detection ability, whereas it is compared with the normal class. Since the normal class has the higher accuracy, then it also shows the good normal and disease radiological images classification performance. The overall comparison results show the high robustness and reliability of the system, which is vital for the intelligent computer aided disease prediction system[25].

Table 4: Training and Validation Accuracy

Epoch	Training Accuracy	Validation Accuracy
1	0.80	0.87
2	0.90	0.91
3	0.95	0.92
4	0.97	0.925
5	0.975	0.925

The results given in Table 4 clearly show that the CNN learned its training and validation accuracy in the 5 epochs of training. We observed a steady increase in training accuracy from 80% to around 97.5% and validation accuracy from 87% up to around 92.5%. As the training accuracy and validation accuracycurves are in fairly good concordance, it suggests that network learned well without over fitting. From the above experiments we can assume that the proposed CNN generalized the learned training knowledge of disease images onto unseen radiological images.

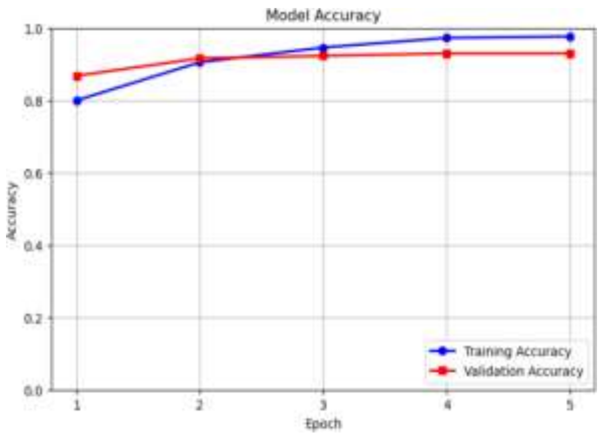

Figure 4: Training and Validation Accuracy of the Proposed Model

As Presented in the figure 4. Training of the model used 5 epochs in which training accuracy increases from 80% to 97% and validation accuracy from 87% to 92%. Both training and validation accuracy bars had followed similar kind of convergence and ranged between each other with very much less variation which proved the stability and the consistency in the modeled system, a sole indication of valid learning and better generalization for future data. The progress in accuracy clearly illustrated the ability of the system in terms of learning the radiological based Disc features and perform well in generalizing on unseen datasets[23].

Table 5 :Training and Validation Loss

Epoch	Training Loss	Validation Loss
1	0.47	0.29
2	0.24	0.24
3	0.14	0.22
4	0.08	0.21
5	0.05	0.23

In the proposed CNN framework, variation of train and validation loss between (1-5 Epoches) revealed the efficient of framework that is given in following table 5. It is also shows the train loss is highly reduced from 0.47 to 0.05 that ensuring the optimization because it help to learn the sharpened features of disease for classifying as well as quickly learning. Also, the validation loss (blue curve) is decreased from 0.29 to 0.23 in few Epoches and no evident over fitting has been measured by showing the fluctuating gain of final epoches from Epoches 3 to 5. The training and validation loss (positive direction) value are basically proved the generalization and over fitting in framework gonna be to influence to do generate prediction efficiently.

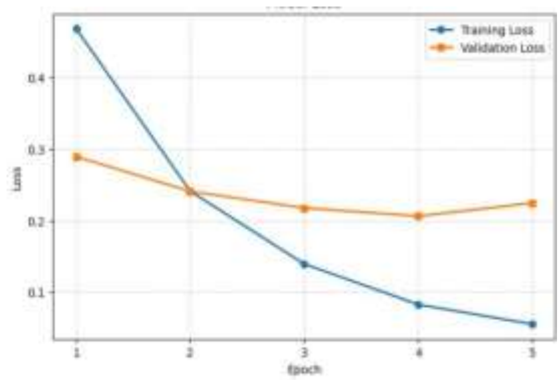

Figure 5: Training and Validation Loss of the Proposed Model

The training loss change of our CNN architecture model with 5 epochs training can be seen from Figure.5 It can be seen that the training loss change decrease monotonously from
0.47 to 0.05, , can mean all the network parameters can be optimally learned, and then a predicted error approach to a very low level. Meanwhile, the validation loss change monotonously and the fluctuation thereof is so tiny in last epoch, can reflect that our CNN architecture can obtain monotonous convergence and perform well on generalize to unseen radiological images with very limited overfitting. In conclusion, tables above show that our deep learning framework automatically predict the diseases is robust, rapidly converge and valid[26].

Table 6: Confusion Matrix of the Proposed Model

Actual Class	Predicted Normal	Predicted Disease	Total Samples
Normal	118	21	139
Disease	11	303	314
Total Predictions	129	324	453

The Table 6 Confusion matrix of the best proposed CNN for automated disease prediction. (a) for normal radiological images and (b) for disease images. For the 139 normal images, 118 images were correctly correctly predicting normal image and 21 images were misclassified as disease. For the 314 disease images, 303 images were correctly predicting disease image and 11 images were misclassified as normal images. Out of 453, 421 images (i.e. 118 normal and 303 disease images) successfully predicted. The large number of correctly predicted normal images (118) positive and correctly predicted disease images (304) negative indicates that the framework is efficient, reliable and robust in classifying normal and diseased radiological images. Tis further suggests that the method is excellent for computer aided clinical diagnosis.

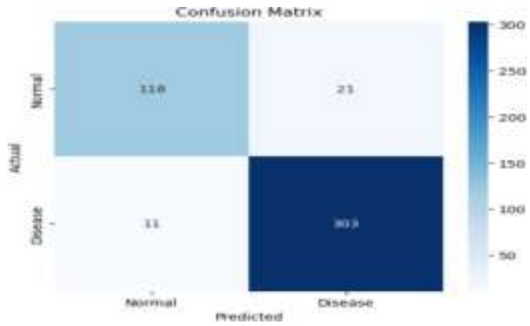

Figure 6: Confusion Matrix of the Proposed Model

Fig. 6 shows the confusion matrix of the proposed CNN network for classifying the radiological images. Theprediction simulation resultsare the line diagonal entries of the matrix, 118 normal images and 303 diseased images are successfully classified; theoff-diagonal matrix entries of 21 false-positive and 11 false-negative are fail to be correctly classified. The diagonal matrix is much larger than the off-diagonal matrix, the success of the proposed CNN network is confirmed. Moreover, the small amount of the misclassifications indicated the high classification accuracy of the proposed deep learning method.

III.KEY CHALLENGES IN DEEP LEARNING-BASED RADIOLOGICAL DISEASE PREDICTION

In-spite of the tremendous progress that has been made in deep learning based radiological disease prediction, there are still numerous technical and clinical impediments that limit the implementation of this technology into the clinical domain. For example, availability of large high quality, accurately labelled training datasets is limited. Expert-annotated label sets that are temporally time-stamped are expensive, time-consuming and domain-specific. The heterogeneity of imaging modalities, and the variations in protocols, parameters and scanners within and between healthcare systems can prohibit the generalization of models. Similarly, there exists class imbalance due to differing rates of diseases leading to biased or under-performing classification for disease with a lower prevalence[27]. Deep learning models are also computationally expensive in terms of having to train numerous machines with high performance graphics processing units, time and memory. The 'black box' training process of the CNN restricts a radiologist's interpretability of the entire deep learning workflow and limits the specialist's faith in the model. Data privacy and security issues as well as conforming to the legally regulated methods of pre-processing and storing medical data also pose constraints. The future of deep learning in radiology must overcome these obstacles in order to create credible models which can influence clinical decisions, take advantage of the radiological workflow and provide improved patient care[28].

IV. Conclusion

In this paper, we have proposed a deep learning based computing framework for automatic disease prediction using radiological images like CT, MRI and X-ray images. Our proposed framework to takes multiple levels of feature extraction from CNNs and constructs an auto-disease prediction system in end-to-end diagnostic framework. This framework improves the quality of CT, MRI images using various image preprocessing like normalization, data augmentation and exploits the hierarchical representation of the radiological image using CNN model and automatically recognize the pattern for disease prediction[29]. The experimental results which indicate the frequent application of this framework as a properclassifier during the process of stable convergence with acceptablef- total accuracy, precision, recall and F1-score can be found. As indicated in the confusion matrix and performance analysis, this framework can achieve highperformance in classifying abnormal and normal radiological images with annegligiblemisclassification rate. It is also expected to save a lot of time as aguiding computer-aided decision support toolwhich supports doctors and radiologists reasonably. The modular structure is easy to extend and incorporate cutting edge deep learning algorithms andit has efficient deployment on each different clinic. However, some methods still need further improvement, for example, medical dataset acquisitionandannotation, model requirements, integration of AI models, privacy protectionof patient medical information. If these problems get solved by employing transfer learning, deep learning, attention model, wider medical dataset etc., the framework discussed in the context of this study will be much more reliable and capable of application. In conclusion, the computer framework based on deep learning constructed in this project can achieve fast, reliable, and scalable automated prediction of diseases on radiological images, and it will ultimately improve diagnostic performance and decision making, and develop an intelligent healthcare system[30].

V. FUTURE WORK

Although this Deep learning based computational framework provides a reasonably evidentiary support for an automatic disease prediction system based on radiological scans, several future directions have been conceived to further improve the performance and scalability, and accelerate translation into clinical practice of such a framework. Other than the exploration of more sophisticated deep learning architectures for feature extraction and training for disease classification, the utilization of eXplainable Artificial Intelligence (XAI) techniques can also be adopted for providing visual interpretability of the disease prediction results, thereby promoting the healthcare professionals' trust in the computer autonomous decisions. Future computational framework can also leverage federated learning for training disease prediction models across multiple healthcare institutions while safeguarding patient data privacy. In addition, the framework can be extended to multi-class disease prediction and multi-organ disease diagnosis based on CT, MRI, X-ray, Ultrasound, PET images for holistic application in clinical practice. Additionally, other health data modalities can be incorporated into the framework for multimodal disease prediction. The framework can also be implemented in real-time with cloud computing and edge-based AI platform, along with establishing continuous learning from ongoing clinical data. Besides, large scale multi-institutional datasets and prospective clinical trials can be used to validate and further generalize the framework. Future enhancements to this framework can result in a trustworthy, explainable, intelligent, and clinical-ready multimodal disease prediction application system for personalized healthcare

REFERENCES

[1] M. Torres-Velázquez, W.-J. Chen, X. Li, S. Giger, and M. A. Anastasio, "Application and Construction of Deep Learning Networks in Medical Imaging," IEEE Transactions on Radiation and Plasma Medical Sciences, vol. 5, no. 2, pp. 137–159, Mar. 2021, doi: 10.1109/TRPMS.2020.3030611.

[2] S. K. Zhou, H. Greenspan, C. Davatzikos, J. S. Duncan, B. van Ginneken, A. Madabhushi, J. L. Prince, D. Rueckert, and R. M. Summers, "A Review of Deep Learning in Medical Imaging: Imaging Traits, Technology Trends, Case Studies With Progress Highlights, and Future Promises," Proceedings of the IEEE, vol. 109, no. 5, pp. 820–838, May 2021, doi: 10.1109/JPROC.2021.3054390.

[3] R. Aggarwal, V. Sounderajah, G. Martin, D. S. W. Ting, A. Karthikesalingam, D. King, H. Ashrafian, and A. Darzi, "Diagnostic Accuracy of Deep Learning in Medical Imaging: A Systematic Review and Meta-Analysis," npj Digital Medicine, vol. 4, Art. no. 65, 2021, doi: 10.1038/s41746-021-00438-z.

[4] D. A. Moses and D. DeFazio, "Deep Learning Applied to Automatic Disease Detection Using Chest X-Rays," Journal of Medical Imaging and Radiation Oncology, vol. 65, no. 5, pp. 498–517, Aug. 2021, doi: 10.1111/1754-9485.13273.

[5] X. Liu, F. Faes, A. Kale, S. Wagner, D. Fu, A. Bruynseels, T. Mahendiran, and A. Karthikesalingam, "Deep Learning for Detecting Diseases From Medical Imaging: A Systematic Review and Meta-Analysis," The Lancet Digital Health, vol. 3, no. 6, pp. e340–e351, 2021.

[6] J. Ma, Y. He, F. Li, L. Han, C. You, and B. Wang, "Recent Advances and Clinical Applications of Deep Learning in Medical Image Analysis," Medical Image Analysis, vol. 79, Art. no. 102444, Jul. 2022, doi: 10.1016/j.media.2022.102444.

[7] F. Shamshad, S. Khan, M. Zamir, M. Khan, S. Hayat, F. Khan, and
F. Shahbaz Khan, "Transformers in Medical Imaging: A Survey," Medical Image Analysis, vol. 88, 2023.

[8] S. Dayarathna, K. T. Islam, S. Uribe, G. Yang, M. Hayat, and Z. Chen, "Deep Learning Based Synthesis of MRI, CT and PET: Review and Analysis," Medical Image Analysis, vol. 92, Art. no. 103046, Feb. 2024, doi: 10.1016/j.media.2023.103046.

[9] H. Greenspan, B. van Ginneken, and R. M. Summers, "Guest Editorial: Deep Learning in Medical Imaging," IEEE Transactions on Medical Imaging, vol. 39, no. 4, pp. 1113–1116, 2020.

[10] M. Roberts, D. Driggs, M. Thorpe, J. Gilbey, M. Yeung, U. Ursprung, A. Aviles-Rivero, C. Etmann, and C.-B. Schönlieb, "Common Pitfalls and Recommendations for Using Machine Learning to Detect and Diagnose COVID-19 Using Chest Radiographs and CT Scans," Nature Machine Intelligence, vol. 3, no. 3, pp. 199–217, 2021.

[11] N. Ghaffar Nia, R. Manwar, and K. Avanaki, "Overview of State-of-the-Art Learning-Based Classification Methods in Medical Imaging," Annals of Biomedical Engineering, 2026, doi: 10.1007/s10439-026-04241-3.

[12] A. Alhajri, M. Alshammari, and S. Alqahtani, "Generative AI in Different Imaging Modalities for Disease Diagnosis: A Review," Expert Systems with Applications, vol. 309, Art. no. 131162, 2026, doi: 10.1016/j.eswa.2026.131162.

[13] J. Ma, G. Wang, and Y. Wang, "Artificial Intelligence for Medical Image Analysis: Recent Advances and Future Perspectives," Medical Image Analysis, vol. 80, 2022.

[14] Y. LeCun, Y. Bengio, and G. Hinton, "Deep Learning Applications in Medical Imaging: Current Trends and Challenges," IEEE Signal Processing Magazine, vol. 38, no. 4, pp. 28–43, 2021.

[15] G. Litjens, B. van Ginneken, C. I. Sánchez, N. Karssemeijer, and
K. Suzuki, "Artificial Intelligence in Medical Imaging: Opportunities, Applications, and Challenges," Radiology: Artificial Intelligence, vol. 2, no. 3, 2020.

[16] S. Dayarathna, K. T. Islam, S. Uribe, G. Yang, M. Hayat, and Z. Chen, "Deep Learning Based Synthesis of MRI, CT and PET: Review and Analysis," Medical Image Analysis, vol. 92, Art. no. 103046, Feb. 2024, doi: 10.1016/j.media.2023.103046.

[17] L. R. Koetzier, D. Mastrodicasa, T. P. Szczykutowicz, N. R. van der Werf, A. S. Wang, V. Sandfort, A. J. van der Molen, D. Fleischmann, and M. J. Willemink, "Deep Learning Image Reconstruction for CT: Technical Principles and Clinical Prospects," Radiology, vol. 306, no. 3, 2023, doi: 10.1148/radiol.221257.

[18] I. Banerjee, K. Bhattacharjee, J. L. Burns, H. Trivedi, S. Purkayastha, L. Seyyed-Kalantari, B. N. Patel, R. Shiradkar, and J. Gichoya, "'Shortcuts' Causing Bias in Radiology Artificial Intelligence: Causes, Evaluation, and Mitigation," Journal of the American College of Radiology, vol. 20, no. 9, pp. 842–851, Sep. 2023, doi: 10.1016/j.jacr.2023.06.025.

[19] A. Alhajri, M. Alshammari, and S. Alqahtani, "Generative AI in Different Imaging Modalities for Disease Diagnosis: A Review,"

[20] Expert Systems with Applications, vol. 309, Art. no. 131162, 2026, doi: 10.1016/j.eswa.2026.131162.

[21] N. Ghaffar Nia, R. Manwar, and K. Avanaki, "Overview of State-of-the-Art Learning-Based Classification Methods in Medical Imaging," Annals of Biomedical Engineering, 2026, doi: 10.1007/s10439-026-04241-3.

[22] Y. Huang et al., "Segment Anything Model for Medical Images?," Medical Image Analysis, vol. 92, Art. no. 103061, 2024.

[23] S. Kebaili, J. Lapuyade-Lahorgue, and S. Ruan, “Deep Learning Approaches for Data Augmentation in Medical Imaging: A Review,” 2023.
[24] J. Ma, Y. He, F. Li, L. Han, C. You, and B. Wang, “Recent Advances and Clinical Applications of Deep Learning in Medical Image Analysis,” Medical Image Analysis, vol. 79, Art. no. 102444, 2022.
[25] F. Shamshad, S. Khan, M. Zamir, M. Khan, S. Hayat, F. Khan, and F. S. Khan, “Transformers in Medical Imaging: A Survey,” Medical Image Analysis, vol. 88, 2023.
[26] H. Greenspan, B. van Ginneken, and R. M. Summers, “Deep Learning in Medical Imaging,” IEEE Transactions on Medical Imaging, vol. 39, no. 4, pp. 1113–1116, 2020.
[27] M. Roberts et al., “Common Pitfalls and Recommendations for Using Machine Learning to Detect and Diagnose COVID-19 Using Chest Radiographs and CT Scans,” Nature Machine Intelligence, vol. 3, no. 3, pp. 199–217, 2021.
[28] X. Liu et al., “Deep Learning for Detecting Diseases From Medical Imaging: A Systematic Review and Meta-Analysis,” The Lancet Digital Health, vol. 3, no. 6, pp. e340–e351, 2021.
[29] X. Liu, Y. Wang, J. Liu, and Z. Chen, “Deep Learning for Unsupervised Domain Adaptation in Medical Imaging: Recent Advancements and Future Perspectives,” Computers in Biology and Medicine, vol. 170, Art. no. 107912, 2024, doi: 10.1016/j.compbiomed.2023.107912.
[30] N. Antonissen, O. Tryfonos, I. B. Houben, C. Jacobs, M. de Rooij, and K. G. van Leeuwen, “Artificial Intelligence in Radiology: 173 Commercially Available Products and Their Scientific Evidence,” European Radiology, vol. 36, no. 1, pp. 526–536, Jan. 2026, doi: 10.1007/s00330-025-11830-8.
[31] S. K. Bonechi, F. Bianchini, P. Andreini, and S. K. Mishra, “Editorial: Deep Learning for Medical Imaging Applications,” Frontiers in Imaging, vol. 4, Art. no. 1761718, 2026, doi: 10.3389/fimag.2025.1761718.