Disease Prediction Based On Medical Images Using Deep Learning

Kasarapu Ramani*[1], Ganesh Sushma Sree[2], Boya Sai Priya [3], Battamdoddi Sampurna[4], Karnati Shashi Vardhan Reddy[5]
[1]Professor, Dept. of Data Science, Mohan Babu University (Erstwhile Sree Vidyanikethan Engineering College),Tirupati. India
[2,3,4,5] UG Scholar, Department of Computer Science and Systems Engineering, Sree Vidyanikethan Engineering College, Tirupati, India.

*head-ds@mbu.asia
sushmasree713@gmail.com
saipriya17102@gmail.com
sampurna1199@gmail.com
karnatikarnatishashi@gmail.com

Abstract. Disease prediction based on medical images is a crucial area of research in healthcare. This study compared two Deep Learning methodologies through a comparative analysis: Convolutional Neural Networks (CNN) and Xception for disease prediction using a dataset of Medical Images. The dataset consists of total 5000 images to train and evaluate both CNN and Xception models and the evaluation metrics include Accuracy, Precision, F1-Score, and Recall. Our findings showed that Xception outperformed CNN in all these metrics, indicating its superior ability to accurately predict diseases from medical images. Additionally, we classified the levels of disease risk according to the models' predictions. The risk levels were classified as low, moderate, and high, allowing for a better understanding of the potential severity of the diseases. Additionally, we proposed further steps that could be taken based on the disease risk level predictions. These measures encompassed dietary adjustments and precautionary measures aimed at mitigating individuals' risk of developing the diseases. Moreover, we discussed potential treatment methods that could be pursued depending on the disease predictions, providing a comprehensive approach to disease prevention and management.

Keywords: Disease prediction, Medical Images, Deep Learning, Convolutional Neural Networks (CNN), Xception.

1 Introduction

In today's era, disease prediction has become an essential aspect of healthcare, with advancements in technology revolutionizing the way we approach diagnosis and treatment. Traditional methods of disease prediction have been effective but are often time-consuming and may lack precision. Consequently, there has been a rising interest in utilizing deep learning methodologies like Convolutional Neural Networks (CNN) and Xception for predicting diseases from

K. R. Madhavi et al. (eds.), *Proceedings of the International Conference on Computational Innovations and Emerging Trends (ICCIET 2024)*, Advances in Computer Science Research 112,
https://doi.org/10.2991/978-94-6463-471-6_24

medical images. CNN and Xception are two popular deep learning architectures known for their ability to process and analyze images effectively. Due to their ability to learn hierarchical image representations and extract relevant features, deep learning techniques like Convolutional Neural Networks (CNN) and Xception have found extensive use across diverse fields, with medical image analysis being a prominent example. Utilizing these deep learning techniques facilitates the creation of models that accurately forecast diseases from medical images, presenting a faster and more precise option compared to traditional methods.

The approach of Convolutional Neural Networks (CNN) entails the extraction of features via layered filters, thereby efficiently acquiring spatial relationships. CNNs act like detectives, using stacked layers to extract subtle clues (features) from images. Xception takes a different approach, efficiently analyzing information by separating feature extraction and combination steps. Among these two, we pull out the model that predicts Medical Images effectively also provide Risk Level, Dietary Modifications, Precautions and Treatment Methods for the respective disease.

2 LITERATURE REVIEW

In [1], a deep learning model detected early pneumonia from chest X-rays, showing promise. However, its reliance on extensive annotated datasets posed a challenge, particularly for rare conditions like pneumonia, leading to limited generalization and reduced accuracy. This constraint impedes its efficacy in practical use cases.

In [2], a deep learning-based system was devised for automatically detecting Alzheimer's disease by employing structural magnetic resonance imaging data. However, the limitation lies in the training of the model's predictions, and it does not have accuracy as our model poses.

In [3], a newly introduced deep learning framework was proposed for automatically diagnosing cervical cancer using Pap smear images. The limitation emerged from the sensitivity of the model to image quality and variations in sample preparation techniques, affecting its generalizability across different healthcare settings.

In [4], a framework for automatic detection of diabetic retinopathy using deep learning with uncertainty quantification was introduced. Despite its potential, the model's performance may degrade in the presence of noisy or low-quality retinal images, limiting its reliability in real-world clinical settings.

In [5], the work by Suganya devi et al. (2022) explores the potential of deep learning for diabetic retinopathy detection. However, a potential limitation identified in their study is the availability of data. As with dermatology datasets, access to large-scale, high-quality fundus image datasets specifically designed for diabetic retinopathy analysis might be limited. This could restrict the training and evaluation processes for deep learning models, potentially hindering their generalizability and overall performance.

In [6], convolutional neural networks (CNNs) were employed for retinal vessel segmentation and glaucoma detection. Despite their effectiveness, the main limitation arises from the model's sensitivity to image quality and variations in retinal imaging protocols, leading to suboptimal performance and generalizability across different clinical settings.

In [7], a comprehensive review of deep learning techniques for tuberculosis detection using chest X-rays was presented. The limitation stems from the model's susceptibility to biases inherent in the training data, potentially leading to disparities in disease detection across different demographic groups.

In [8], a survey was conducted regarding the application of artificial intelligence (AI) methodologies for diagnosing diseases through the analysis of medical images. Despite the diverse range of algorithms explored, the limitation lies in the lack of standardized evaluation metrics and benchmarks, hindering fair comparisons between different models.

In [9], there was a survey that concentrated on deep learning algorithms for the analysis of medical images, demonstrating their usage across a broad spectrum of medical specialties. However, the limitation arises from the computational complexity of deep learning models, which may require significant computational resources for training and deployment.

In [10], an effective transfer learning model was introduced for the categorization of the corona virus disease using thoracic radiographs. Despite its effectiveness, the limitation arises from the model's dependency on pre-trained weights, which may not capture domain-specific features relevant to COVID-19 diagnosis, leading to suboptimal performance in certain cases.

From the above literature survey it is to be found that the disease prediction is done for only one or two diseases .But the present research work considers to predict 15 different kinds of diseases also provide further steps to be taken to cure the disease.

3 Methodology

Though medical imaging has become essential for diagnosis and treatment, analyzing large datasets requires significant time and is susceptible to human error. This research work attempts to predict diseases also provide potential dietary modifications and precautions that individuals could take to reduce their risk of developing diseases based on the predictions. Additionally, we explored treatment methods that could be pursued depending on the disease predictions, providing a comprehensive approach to disease prevention and management.

Disease Dataset Overview

The dataset underwent partitioning into training and testing subsets, with 80% designated for training and 20% for testing. Within the set designated for training., there were 3500 images spread across 15 distinct classes, while the testing set contained 1500 images, also categorized into the same classes. Examples of these classes include brain glioma, breast malignant, fractured, glioma, kidney normal, kidney tumor, oral normal, oral scc, and pituitary[10]. Furthermore, an additional dataset provided details on risk levels, dietary suggestions, treatment methods, and precautions related to each medical condition. This supplementary data enhanced the analysis by providing insights into personalized health care strategies based on predictions from input medical images. The integration of these datasets facilitated a thorough investigation of disease prediction and management within the domain of medical imaging analysis.

Data Pre-processing

The data pre-processing steps were carried out on the image dataset for training and validation in the model: Image Resizing, Data Augumentation, Normalization, Categorical Encoding, Batching. Standardizing the size of all images to (224, 224) pixels, ensures a consistent input size for the model. Data Augumentation is done by an 'ImageDataGenerator' which isused to artificially increase the dataset size by randomly applying transformations like rotations, flips, and zooms to the images. The normalization of image pixel values entails dividing them by 255, thereby adjusting them to a scale between 0 and 1. This improves the training process and convergence of the model. The class labels linked to each image are subjected to categorical encoding, which converts them into one-hot encoded vectors, enabling effective handling of multi-class classification tasks. Batching the Images into size of 16 during training and validation. This improves training efficiency by utilizing available memory effectively.

Algorithm: Convolutional Neural Networks(CNN)

This study employs Convolutional Neural Networks (CNNs) [11] as the operational framework for disease prediction using medical images. It incorporates multiple convolutional layers and pooling layers [6], alongside a singular fully connected layer, to train the image dataset. The process involves several steps:

- Initially, the Sequential model is initialized, enabling the sequential addition of layers.
- Conv2D layers are added to capture features from input images. Key parameters like filter size, activation function ('relu'), and stride are defined.
- MaxPooling2D layers are inserted after some Conv2D layers to down sample the data and manage model complexity.
- Following the convolutional and pooling layers, a Flatten layer is introduced to reshape the data into a one-dimensional array.
- Dense layers are employed for classification tasks, utilizing the extracted features. The final Dense layer utilizes 'softmax' activation to produce class probabilities for accurate classification[12].
- During compilation, the model is configured with the 'Adam' optimizer and employs the 'categorical cross-entropy' loss function. Additional evaluation metrics are designated to evaluate the model's performance throughout the training phase.

- Training the model with the fit() method involves learning from the training data generator (train_gen) and validating using the validation data generator (val_gen).
- Parameters like steps_per_epoch and validation_steps are set to control the number of batches processed during each epoch for training and validation, respectively.

Algorithm: Xception

In the realm of disease prediction with medical images, the Xception algorithm approach to predict diseases consists of Input layer, Depth-Wise Seperable Convolutional layer, Normalization Layer, Pooling layers and Prediction layer. The subsequent steps outline the process of training and evaluating the model:

1. Convolutional Blocks:
   - The neural network architecture consists of 14 blocks, each pivotal in feature extraction and representation learning. In every block, a structured procedure unfolds across six stages.
   - Initially, specific patterns are captured through convolutional operations tailored to the input data.
   - Subsequently, batch normalization is applied to stabilize and enhance training efficiency.
   - An activation function follows, introducing non-linearity for modeling complex data relationships.
   - This is succeeded by another convolutional layer, refining learned features further.
   - Batch normalization is reapplied to maintain gradient stability.
   - Finally, another activation function ensures the network's ability to learn intricate representations.

Through this iterative process, hierarchical features are progressively extracted, enabling the model to discern subtle patterns and nuances in the input data. This enhancement ultimately improves the model's accuracy in making predictions and classifications[5].

2. The global_max_pooling2d layer executes a global max-pooling operation across the spatial dimensions of the input tensor (block14_sepconv2_act). It condenses the information for each feature map into a single value by extracting the maximum activation from every feature map across all spatial locations.

3. The flatten_1 layer reshapes the output obtained from global max-pooling into a 1-dimensional tensor. This stage unifies the spatial dimensions of the pooled feature maps into a single vector, readying the data for subsequent processing by fully connected layers [13].

4. The dense_3 layer, a fully connected (dense) layer comprising 15 units, processes the flattened output from the preceding layer. This layer implements a linear transformation, followed by applying the 'Relu' activation function to generate the final output. Typically serving as the output layer, it facilitates predictions or classifications based on the features learned by the preceding layers.

5. After training the model is set to run epochs and the evaluation measures are calculated at the end. The models are saved, and performance metrics are retrieved from each model for further comparative analysis. The proposed methodology is illustrated in Fig 1.

Formulation for Performance Metrics

The performance of CNN and Xception models are compared using evaluation metrics.

$$Accuracy = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \tag{1}$$

$$Precision = \frac{\text{True Positives}}{\text{True Positives+False Positives}} \tag{2}$$

$$Recall = \frac{\text{True Positives}}{\text{True Positives+False Negatives}} \tag{3}$$

$$F1 - Score = 2 \times \frac{\text{Precision} \times \text{Recalll}}{\text{Precision+Recal}} \tag{4}$$

Architecture of Proposed System

The Proposed Architecture of the system is described in the below Fig 1.

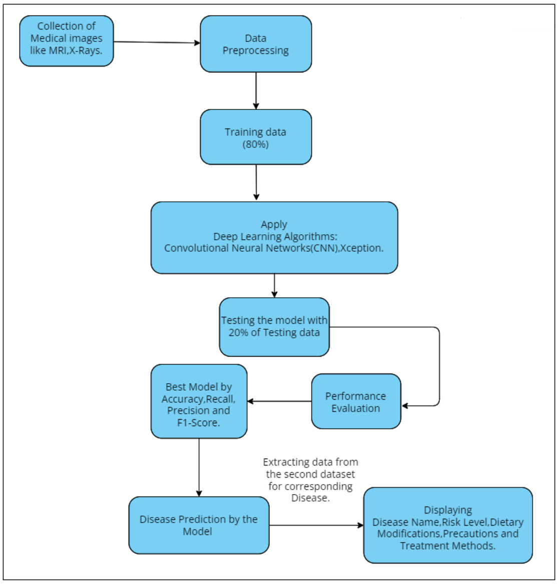

Fig 1: Proposed Architecture

Comparison of Proposed System and Existing System

In our comparison, the proposed system demonstrates higher accuracy levels when contrasted with the existing system. Utilizing automation and advanced algorithms, it enhances precision and reliability, reducing errors in decision-making and reporting. This improvement assures more dependable outcomes, fostering trust and credibility within our operations. By effectively leveraging technology, the proposed system elevates overall performance, underscoring its potential to substantially enhance accuracy and efficiency in our work processes. The details of the comparison can be observed in the Table 1 below.

Table 1: Comparision of Existing and Proposed Work

Work	Accuracy
S. Suganya devi, K.Renukadevi	87.5%
Qing Zeng Song, Lei Zhao	88.2%
Proposed Model	91.33%

4 Results

For the implementation of this research work, Intel Core i5,with RAM 6 GB and Hard disk of 520GB and Python 3.8 is used. The Medical Images dataset consists of total 5000 images in which 15 diseases are classified. The Convolutional Neural Networks (CNN) and Xception model's are applied on the medical images dataset and the disease prediction is done. The obtained results are shown in Fig 2.

We can also observe that the Bar Graph of Xception model is high when compared to Convolutional Neural Networks(CNN). The dataset comprises 5000 images, partitioned into 80% for training and 20% for testing, covering a total of 15 diseases categorized for disease identification. Based on the medical image that is provided to identify the image the model examines the features of the image and predict the disease. Another dataset in which all the dietary modifications, risk level, precautions and treatment methods are classified to all the 15 diseases. The predicted disease's corresponding dietary modifications, risk level, precautions and treatment methods are shown along with the disease name as a result. The comparision of model's is shown in Fig 2.

The performance of two deep learning architectures, Convolutional Neural Networks (CNN) and Xception are compared in Fig 2 predicting diseases from medical images. The models were assessed using four principal metrics: Accuracy, F1-Score, Precision, and Recall[14].

Table 2:Performance Metrics of CNN and Xception

Model	Xception	CNN
Accuarcy	0.9133	0.7297
Recall	0.9213	0.9212
Precision	0.9018	0.6524
F1-Score	0.9110	0.7590

The figure above Fig 2 shows the graphical representation of comparision of models. All the Performance Metrics(1)(2)(3)(4),values are less than 1 which represents that the models are perfectly trained with the medical images dataset.

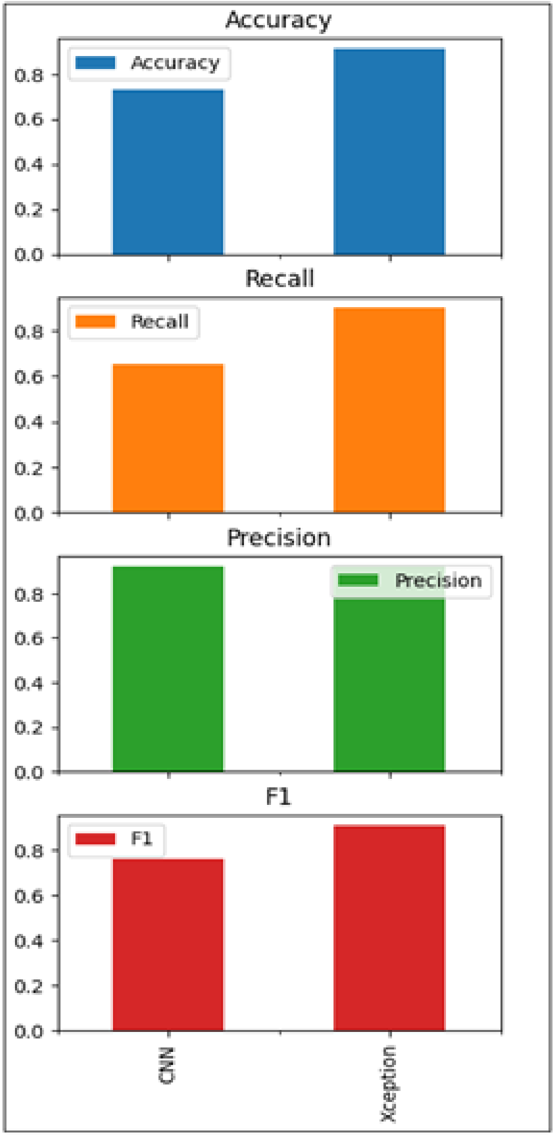

Fig 2 : Comparision of CNN and Xception

In evaluating the efficiency of our disease prediction models, as outlined in Table 1, we focused on evaluation measures, with Xception representing our proposed algorithm. The analysis demonstrate that the Xception model outperforms other models across all four metrics, attaining a Accuray of 0.9133, Precision of 0.9213, Recall of 0.9018 and F1-Score of 0.9110.These analysis of models underscore the significance of our proposed Xception algorithm in enhancing the overall efficiency of the disease prediction based on medical images[15], providing substantial improvements across multiple performance measures.

In this study, we sought to predict diseases using medical images and then provide personalized dietary recommendations, precautions and Treatment Methods based on the identified health conditions. Focusing on health issues like Tumors, Fractures, Pituitary disease, Breast disease and Oral diseases, our approach aimed to offer tailored dietary advice that aligns with individual health needs. Our results demonstrated that the Xception deep learning model outperformed the Convolutional Neural Networks (CNN)[16] in predicting diseases from medical images.

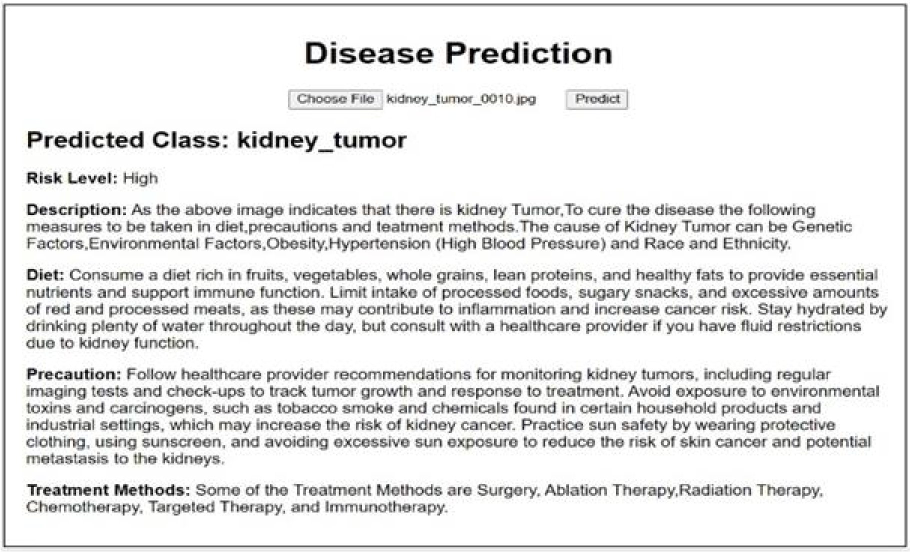

Fig 3:Disease Prediction by Xception Model.

Through our approach, individuals received dietary recommendations specific to their health conditions, empowering them to make informed choices and positively impacting their overall well-being. Our study also provide the risk level of the predicted disease, precautions to be taken to cure the disease and also treatment methods for the disease predicted as shown in Fig 3.

5 Conclusion

In conclusion, our research unequivocally demonstrates Xception's superiority over Convolutional Neural Networks in predicting diseases from medical images. The categorization of disease risk levels based on our models' predictions furnishes valuable insights into disease severity, enabling tailored interventions. This underscores Xception's potential to redefine diagnostic accuracy and patient care in healthcare. Moreover, actionable recommendations such as dietary adjustments and lifestyle modifications, provide pragmatic avenues for disease prevention. Integrating Deep Learning-based predictions with personalized interventions signifies a significant leap forward in healthcare management strategies. This study establishes a ground work for future investigations focused on refining disease prediction models and improving patient outcomes. Ultimately, our research contributes to the ongoing endeavor of leveraging technology to enhance healthcare delivery and advance public health outcomes.

6 References

1. Agrawal, R., Prakaash, R., & Mittal, M. A deep learning model for early pneumonia detection from chest X-rays. In 2020 6th International Conference on Advanced Computing and Communication Systems (ICACCS) (pp. 793-797). IEEE(2020).
2. Ahmad, R., Khan, M. A., Hussain, A., & Sharma, D. K. Deep learning based system for automatic detection of Alzheimer's disease using structural magnetic resonance imaging data. Archives of Medical Research, 51(8), 555-561(2020).
3. Das, S., Kar, S., & Majumder, D. D. A novel deep learning framework for automated cervical cancer diagnosis using Pap smear images. Journal of Medical Imaging and Health Informatics, 12(8), 3570-3577(2022).
4. Das, S., Sharma, N., & Majumder, D. D. A framework for automatic detection of diabetic retinopathy using deep learning with uncertainty quantification. International Journal of Medical Engineering and Informatics, 14(3), 206-219(2023)
5. S. Suganya devi, K. Renukadevi, K.Balasamy, P.Jeevitha . Diabetic Retinopathy Detection Using Deep Learning Techniques .First International Conference on ICEEICT (2022).
6. Jagannathan, S., Rao, R. K., & Murthy, N. P. Convolutional neural networks for retinal vessel segmentation and glaucoma detection. Journal of Medical Imaging and Health Informatics, 10(2), 965-972(2020).
7. Kumari, R., Verma, U., & Sharma, K. A comprehensive review of deep learning techniques for tuberculosis detection using chest X-rays. Artificial Intelligence in Medicine, 135, 109835(2022).
8. Rajput, S., Singh, R., & Kumar, N. A survey on machine learning and deep learning algorithms for disease detection using medical images. Journal of Medical Imaging and Health Informatics, 12(5), 2154-2166(2022).
9. Raju, S. "W-Period Technique for Parallel String Matching." IJCSNS 7, no. 9 (2007): 162.
10. Singh, S., Sinha, B., & Khan, M. A. An efficient transfer learning model for COVID-19 classification using chest X-ray images. Journal of Medical Imaging and Health Informatics, 10(8), 2709-2718(2020).
11. Palanisamy, S., Jahnavi, M. P., & Karthick, B. Deep Learning for Medical Image Analysis: A Review and Future Directions. In Proceedings of the International Conference on Advances in Computing and Communication (pp. 879-887)(2023).
12. Mehta, S., Sharma, G., & Singh, G.A comprehensive review on deep learning based medical image analysis for disease prediction. Journal of Medical Imaging and Health Informatics, 12(3), 1089-1102(2022).
13. Mittal, M., Kumar, A., & Singh, G. (2021). Deep learning for medical image analysis: Applications in neuroimaging. In Intelligent Computing and Optimization (pp. 71-83).
14. Jain, P., Gupta, N., & Gupta, V.Deep learning models for automatic diagnosis of diabetic retinopathy: A survey. Artificial Intelligence in Medicine, 108, 101815(2020).
15. Nair, D., Jacob, S., & Jayasree, P. K. A survey on deep learning models for medical image analysis. In International Conference on Intelligent Computing and Control (pp. 281-290)(2019).
16. Singh, G., Kaur, I., & Mittal, M. Deep learning based medical image analysis: A survey of techniques and applications. In Recent Trends in Image Processing and Pattern Recognition (pp. 147-161)(2018).