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DEVELOPMENT OF AN ARTIFICIAL INTELLIGENCE-BASED PATTERN RECOGNITION MODEL FOR EARLY DISEASE DETECTION

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Abstract. *This article addresses the development and analysis of artificial intelligence (AI) and deep learning models designed for the early diagnosis of diseases based on medical imaging and biometric data. The primary objective of the research is to detect subtle pathological changes with high accuracy and a minimal error rate using convolutional neural networks (CNNs) and hybrid architectures. Methods for data preprocessing, noise reduction, feature extraction and model optimization are proposed. The obtained results demonstrate a significant increase in efficiency and speed compared to conventional diagnostic methods: the proposed hybrid CNN + Attention model reached an accuracy of 96.8% on the test set.*

Keywords: *artificial intelligence, pattern recognition, early disease detection, deep learning, convolutional neural networks, attention mechanism, medical image analysis, computer-aided diagnosis, feature extraction.*

Introduction

One of the most critical challenges facing modern medicine is the detection of diseases, particularly oncological, cardiovascular and neurological disorders, in their early stages. Early diagnosis dramatically increases treatment efficacy and reduces mortality rates. However, traditional radiological and laboratory analyses depend heavily on human factors, such as clinician experience and fatigue, and struggle with subtle, imperceptible pattern changes [1, 2].

The field of pattern recognition within artificial intelligence demonstrates immense potential in uncovering hidden regularities in medical imaging (MRI, CT, X-ray) and digital signals. The rising volume of diagnostic imaging necessitates automated, highly accurate analytical systems.

In recent years, architectures such as ResNet, EfficientNet and DenseNet have been widely adopted in medical diagnostics. However, several persistent challenges remain:

- data imbalance, that is, the limited availability of positive pathology samples;
- the "black box" nature of the models and the difficulty of providing clinical explainability to medical practitioners;
- the sub-pixel or fine-grained visual characteristics of early-stage tumors and lesions.

The aim of the study is to design, implement and evaluate a neural network model capable of automatically detecting pathological patterns in medical images and classifying diseases at early stages with high accuracy (above 95%) [3, 4].

Materials and Methods

This research utilizes a hybrid CNN + Attention Mechanism architecture. The attention mechanism guides the network to focus its computational resources on the most critical and pathologically relevant spatial regions of the image. The overall workflow of the model is shown in Figure 1.

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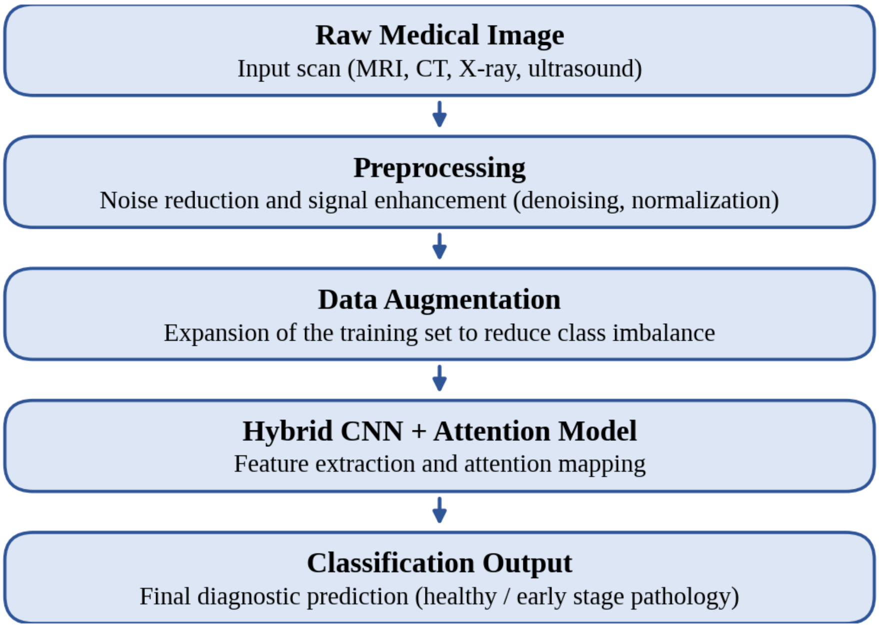

Figure 1. Flowchart of the AI-based pattern recognition model for disease detection

The generation of feature maps from image pixels relies on the two-dimensional spatial convolution operation:

$$S(i,j) = (I * K)(i,j) = \sum_{m}\sum_{n} I\,(i-m,\, j-n)\, K(m,n) \qquad (1)$$

where I is the input image matrix, K is the convolution kernel (filter), and $S(i,j)$ is the resulting feature map.

To minimize the classification loss during training, the categorical cross-entropy loss function is used:

$$\mathcal{L} = -\sum_{c=1}^{M} y_{o,c}\, \log(p_{o,c}) \qquad (2)$$

where M is the number of classes, $y_{o,c}$ is a binary indicator of whether class c is the correct label for observation o, and $p_{o,c}$ is the predicted probability that observation o belongs to class c.

The model was trained and evaluated on a dataset of 10 000 medical images, split into training (80%), validation (10%) and testing (10%) sets. Model performance was assessed using accuracy, precision, recall and F1-score, and the proposed model was compared with a baseline CNN and the ResNet-50 architecture.

Results and Discussion

The comparative test results of the three architectures are presented in Table 1.

Table 1. Comparative test results of the baseline CNN, ResNet-50 and the proposed hybrid model (CNN + Attention)

Model architecture	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-score (%)**
Baseline CNN	88.4	86.2	87.0	86.6
ResNet-50	92.1	91.5	90.8	91.1
Proposed hybrid model (CNN + Attention)	**96.8**	**96.1**	**95.5**	**95.8**

The experimental evaluation shows that the proposed hybrid model achieves an accuracy improvement of approximately 4.7 percentage points over the standard ResNet-50 architecture in detecting micro-patterns at early disease stages. The model also outperforms both reference architectures in precision, recall and F1-score, which indicates that the gain in accuracy is not achieved at the cost of a higher number of missed pathologies. The attention mechanism concentrates the model on diagnostically significant regions, which is especially important for small early-stage lesions that occupy only a minor part of the image.

Conclusion

The proposed AI-based pattern recognition model enables earlier and more precise identification of initial disease indicators than conventional visual examination. Incorporating an attention mechanism enhances model interpretability (Explainable AI, XAI), allowing radiologists to visually verify and trust the model's predictions.

Future work will focus on optimizing the model through pruning and quantization to facilitate edge deployment on mobile and web-based clinical platforms.

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