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Research Article

Acute Myeloid Leukemia (AML) Detection Using AlexNet Model

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Acute Myeloid Leukemia (AML) is a kind of fatal blood cancer with a high death rate caused by abnormal cells' rapid growth in the human body. The usual method to detect AML is the manual microscopic examination of the blood sample, which is tedious and time-consuming and requires a skilled medical operator for accurate detection. In this work, we proposed an AlexNet-based classification model to detect Acute Myeloid Leukemia (AML) in microscopic blood images and compared its performance with LeNet-5-based model in Precision, Recall, Accuracy, and Quadratic Loss. The experiments are conducted on a dataset of four thousand blood smear samples. The results show that AlexNet was able to identify 88.9% of images correctly with 87.4% precision and 98.58% accuracy, whereas LeNet-5 correctly identified 85.3% of images with 83.6% precision and 96.25% accuracy.

1. Introduction

Leukemia is a hematological disorder and type of cancer that weakens the human immune system by generating malignant White Blood Cells (WBC) [1, 2]. Leukemia is considered as one of the fatal cancers with a high death rate [3]. Leukemia is usually classified based on myelogenous or lymphoblastic disorders of the WBCs. If the affected cells are lymphoblastic, then the leukemia is called Acute Lymphoblastic Leukemia (ALL). If the affected WBCs are monocytes and granulocytes, then the leukemia will be called Acute Myeloid Leukemia (AML) [2].

Leukemia is a blood cancer resulting from an abundance of abnormal white blood cells in humans [2]. Usually, a hematology analyzer is used to diagnose leukemia through manual counting. Cell classification usually depends on the morphological characteristics of the cells and requires a skilled medical operator. This procedure can be time-consuming, tedious, and costly [3]. Moreover, the manual analyzer may sometimes lead to the incorrect counting and classification of leukocytes [4]. Undoubtedly, this manual examination mechanism can be replaced by machine-learning-based automated techniques that can save precious time and significantly reduce human effort and error [5, 6].

Deep learning algorithms are powerful and versatile algorithms used efficiently in significant research areas such as medical image processing, supercomputing, investment modeling, and fraud detections [7, 8]. Convolutional Neural Network (CNN) is a popular subcategory of deep learning algorithms, specially designed for visual pattern recognition [9]. LeNet-5 is a CNN-based algorithm that uses seven different layers, including maximum pooling, convolutional, and Fully Connected (FC) [10]. Similarly, AlexNet is a prominent CNN-based algorithm [11] that uses eight

different layers, including maximum pooling, convolutional, and FC [12]. AlexNet is declared the best neural network model for image classification in the Large Scale Visual Recognition Challenge (2012) [13].

In this regard, Thanh et al. [14], Snehal and Daware [15], Liang et al. [16], and Tiwari et al. [17] proposed CNN-based models for leukemia disease detection. Shafique and Tehsin [2], Mishra et al. [18, 19], and Tuba et al. [20] worked on Acute Lymphatic Leukemia (ALL) detection. In contrast, Su et al. [21] and Agaian et al. [22] worked on Acute Myeloid Leukemia (AML) detection. As a limited amount of work is done on Acute Myeloid Leukemia (AML) detection, this work addressed the problem of automatic detection of Acute Myeloid Leukemia (AML) using CNN.

AlexNet algorithm is a competent and well-known deep learning algorithm that can be used efficiently in significant research areas, especially medical image processing [11]. AlexNet can analyze and detect important features from different medical images such as CT scans, X-rays, MRI, PET, ultrasound, and hematological images.

In this work, we proposed an AlexNet-based classification model to detect Acute Myeloid Leukemia (AML) in microscopic blood images and compared its performance with LeNet-5-based model in Precision, Recall, Accuracy, and Quadratic Loss. The experiments are conducted on a dataset of four thousand blood smear samples. The results show that AlexNet was able to identify 88.9% of images correctly with 87.4% precision and 98.58% accuracy, whereas LeNet-5 correctly identified 85.3% of images with 83.6% precision and 96.25% accuracy. In the future, we are planning to apply the AlexNet architecture for other types of leukemia cell detection, such as Acute Lymphatic Leukemia (ALL), to get high accuracy.

This paper is structured as follows. Section 2 discusses a literature review. Section 3 discusses the material and methods used in this work, such as the dataset description, AlexNet architecture, and performance evaluation techniques. Experimental results are discussed in Section 4, and conclusions and future work are discussed in Section 5.

2. Background

2.1. White Blood Cells (WBCs). WBCs (leukocytes) are the human immune system cells that defend the human body against disease, infections, and foreign bodies [23]. WBCs are produced in the bone marrow and derived from hematopoietic stem cells. There are five types of WBCs based on their functional and physical characteristics: lymphocytes, monocytes, eosinophils, basophils, and neutrophils. A brief introduction of all five types of WBCs is as follows:

Lymphocytes create antibodies against various microorganisms such as viruses, bacteria, and other potentially harmful invaders. There are further subtypes of lymphocytes, including B cells, T cells, and natural killer cells.

Monocytes have a longer lifespan, and they help to break down bacteria. The monocyte cell's primary purpose is to present a piece of germ to the T cell to identify it again in future attacks.

Eosinophils rise in the response of disease of nervous systems, collagen, spleen, parasitic infection, and different kinds of allergies, that is, hives and hay fever. However, their primary target is parasites such as tapeworms and hookworms.

Basophils are mainly responsible for antigen and allergic response by releasing histamine (an indication for allergy) that causes the blood vessels to dilate and help the human body for immune response.

Neutrophils act as the first line of defense in case of infection. Their primary purpose is to fight and kill the fungus or bacteria. They are a prevalent cell type seen in the early stages of inflammation, and their activity and death form Pus in the human body.

2.2. Types of Leukemia. Leukemia is a hematological disorder and type of blood cancer that weakens the human immune system by generating a surplus amount of malignant WBCs (White Blood Cells) [1, 2]. Leukemia is usually classified into four major classes based on myelogenous or lymphoblastic disorders: Acute Myeloblastic (Myeloid) Leukemia (AML), Chronic Myeloblastic (Myeloid) Leukemia (CML), Acute Lymphoblastic (Lymphocytic) Leukemia (ALL), and Chronic Lymphoblastic (Lymphocytic) Leukemia (CLL). A brief introduction of all four major types of Leukemia is as follows [24]:

AML is the most common type of leukemia that usually occurs in both adults and children. It affects the WBCs of the human body and causes them to form abnormally. The abundance of abnormal WBCs in the human body causes acute cancers.

ALL is the most common type of cancer in childhood but can also occur in adults. ALL is caused due to the increased lymphocytes (a kind of WBCs) in the human body.

CML is a cancer of WBCs in which immature WBCs or blast cells are formed and multiply uncontrollably in a human body. CML is mostly affecting adults.

CLL is a kind of cancer that affects B lymphocytes or B cells. B cells help the human body fight against infection; however, the cancerous B cells cannot fight infections. CLL usually affects older people.

3. Related Work

AL-Dulaimi et al. conducted a detailed survey WBCs classification techniques for identifying fatal diseases such as blood cancer, AIDS, and leukemia using microscopic images of hematology reports. They also pointed out some crucial challenges in the WBC classification process regarding WBCs structure, image quality, cell morphology, the classification's time complexity, and others [25]. Othman et al. worked on the classification of WBC using feedback and feedforward propagation neural networks. After analyzing

blood cells achieved from telescopic images, the 16 most important elements of that cell were fed as input to the neural network. They trained the neural network with 50% data after segmentation, while the rest of the data are used for testing. They achieved a 96% accuracy in classifying WBCs [26]. Lin et al. pointed out that recognizing the WBCs is difficult due to uneven color and irregular illuminations of blood smear images. They proposed a hybrid model composed of histogram distribution, K-means clustering, watershed algorithm, and CNN for WBCs classification with improved accuracy. They reported that their proposed hybrid model achieved 95.81% accuracy [27]. Umamaheswari and Geetha briefly explained leukemia with all its subtypes and different image segmentation methods used in the machine learning domain to identify leukemia in microscopic images. They concluded their reviews with two significant findings: (i) Machine-learning- and image-processing-based hybrid techniques could offer better results in leukemia detection. (ii) A benchmark dataset is needed to find improvements in the methods proposed from time to time [28].

Thanh et al. proposed a CNN-based classification model for fast detection of acute leukemia disease. In the proposed method, the first classification process is covered in the experimental results, representing an outstanding achievement by differentiating abnormal and normal cells. Their proposed method achieved 96.6% accuracy in leukemia cell classification [14]. Daware proposed an in-depth CNN segmentation-based technique to identify leukemia blood cells in microscopic images. Their proposed methods could classify WBCs in blood smear images with 93.94% accuracy [15]. Liang et al. proposed a combined CNN- and RNN-based blood cell microscopic image classification model to solve the reliance link problem between significant features of images mark and images. They concluded that the proposed CNN and RNN combined model is more precise and accurate than other CNN-based models [16]. Tiwari et al. proposed Double Convolutional Layer Neural Network-(DCLNN-) based blood cells detection model and compared its performance with SVM and Naïve Bayes-based models. They showed that their proposed DCLNN model is more accurate than SVM and Naïve Bayes models [17]. Negm et al. proposed a Decision Support System (DSS) to classify the leukemia cells in microscopic images using K-means clustering and panel selection approach. They conducted experiments with various public and benchmark datasets, and after investigations, they verified their results with expert pathologists. They reported that their system achieved 99.517% accuracy [29].

AlexNet algorithm is a competent and well-known deep learning algorithm that can be used efficiently in significant research areas, especially medical image processing [11]. AlexNet uses eight different layers, including maximum pooling, convolutional, and FC [12]. AlexNet can analyze and detect important features from different medical images such as CT scans, X-rays [30], MRI [31], PET [32], ultrasound [33], and hematological images [34].

3.1. Materials and Methods. This work aims to process and analyze the Acute Myeloid Leukemia smear images to provide an automatic technique to support the medical activity that enables pathologists to segment and recognize Acute Myeloid Leukemia (AML). The research methodology is based on blood smear image analysis for AML classification, using computer vision techniques. The WBCs have five subcategories called monocytes, lymphocytes, basophils, eosinophils, and neutrophils; however, for diagnostics of AML subclass of WBCs, myeloid is used. Therefore, to detect and classify AML, myeloid bodies are easily identifiable from blood smear images, as their nuclei do not look the same from the background and other blood cells. The myeloid, which is affected, is called a myeloid cell, which has additional morphological changes with the syndrome's increasing cruelty. Myeloid is present in regular shape and compact nucleus with having normal and continuous edges. Otherwise, the myeloid has shape irregularities and small nooks/holes in the cytoplasm. Therefore, the proposed procedure will extract the myeloid from the blood smear image, and then CNN features are extracted to classify it as normal or myeloid. We compared the performance of AlexNet with LeNet-5 [35] in terms of Precision, Recall, F-Measure, Accuracy, and Mean Square Error or Quadratic Loss.

The experiments are conducted on a workstation with a 3.1 GHz Core i5 CPU and 8 GB RAM in MATLAB 2018a environment with Deep Learning toolbox [36]. The blood smear pictures are collected from a reputable tertiary care hospital and publicly available microscopic peripheral blood images. In this section, we discuss the dataset, preprocessing steps, AlexNet model, and evaluation parameters.

3.1.1. Dataset. The dataset used in this study comprises four thousand blood smear acute myeloid samples gathered from two different sources, that is, a reputable tertiary care hospital of Peshawar, Pakistan, and publicly available microscopic peripheral blood images released by Acevedo et al. [37]. The dataset consists of 4000 images having 1500 normal monocytes, 1500 abnormal monocytes, and 1000 lymphocytes. The data are preclassified by the experts of the field. The properties of the dataset are available in Table 1.

3.1.2. Data Preprocessing. Data preprocessing is a critical step used to check the data for experiments; before image analysis, the images should be prepared for a good outcome. In our experiments, we resize every image into a 256×256 resolution image. Then they are converted to a 227×227 pixel image to feed it to the first layer of the AlexNet model.

3.1.3. AlexNet Architecture. The AlexNet model comprises five convolutional, three maximum pooling, and three FC layers. The AlexNet model needs a 227×227 resolution image as an input, and then ReLU (Rectified Linear Unit) activation function is applied to remove nonlinearity. After

Table 1: Dataset properties.

Size of images	960 × 1080 pixels
Color model	RGB
Total classes	3
Normal monocytes	1500
Abnormal monocytes	1500
Lymphocytes	1000

that, the images are downsampled to extract rich features using pooling layers. The first FC layer is then used to flatten the feature vector, which drops out 50% of the features. The remaining features are then used for AML disease identification. Each Fully Connected layer contains 4096 neurons. The last FC layer is known as the output layer and will produce 1000 outputs. These 1000 outputs will be passed through the SoftMax activation function. SoftMax activation function or normalized exponential function is used to normalize the network's output to a probability distribution over predicted output classes. In the last phase, we trained and tested our CNN model, which classified different leukemia types that are either normal or abnormal. We apply 30 epochs on training with 5880 iterations. Figure 1 shows the AlexNet model structure, while Table 2 shows the parameters and names of all layers used in the AlexNet model.

3.1.4. Evaluation Parameters. The proposed model's performance is compared with the LeNet-5 model in Accuracy, Precision, Recall, and F-Measure. Precision represents the number of identified images belonging to the correct classes, and Recall represents how the total images are correctly recognized in their respective classes. F-Measure is the harmonic mean of Precision value and Recall value [38, 39]. We also assess the models' performance in Mean Square Error or Quadratic Loss [40].

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}, \tag{1}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}, \tag{2}$$

$$F - \text{Measure} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}, \tag{3}$$

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}}, \tag{4}$$

$$\text{Quadratic Loss} = \frac{\sum_{i=1}^{n} \left(x_i - x_i'\right)^2}{n}. \tag{5}$$

4. Results and Discussion

This research aims to improve the automatic detection of Acute Myeloid Leukemia (AML) in microscopic blood smear images. We proposed AlexNet-based CNN model for accurate detection of AML cells and compared its performance with the LeNet-5-based CNN model. LeNet-5 model is comprised of two convolutional, two maximum pooling, and three FC layers. In contrast, the AlexNet model has five convolutional, three maximum pooling, and three FC layers. The experiments are conducted with the preclassified dataset of 4000 images gathered from a reputable tertiary care hospital of Peshawar, Pakistan, and publicly available microscopic peripheral blood images. The data are preclassified by the experts of the field. The models' performance is evaluated in Precision, Recall, F-Measure, Accuracy, and Mean Square Error or Quadratic Loss.

Based on the experiments' results, the AlexNet-based model was able to correctly classify 88.9% of images with 87.4% precision, whereas LeNet-5 was able to classify 85.3% of images correctly with 83.6% Precision. Similarly, the F-Measure of LeNet-5-based model is recorded as 0.844, whereas, in the case of AlexNet, the F-Measure value is 0.881. The comparison of both LeNet-5- and AlexNet-based models in Precision, Recall, and F-Measure is illustrated in Table 3 and Figure 2.

Similarly, for the accuracy rate of both LeNet-5 and AlexNet models, three classes are illustrated in Table 4 and plotted in Figure 3. According to the results, the accuracy of AlexNet in detecting normal monocytes was 98.88%, whereas LeNet-5 gave 96.69% accuracy for the same class. Similarly, in detecting abnormal monocytes, the accuracies of AlexNet and LeNet-5 were 97.9% and 95.49%, respectively, whereas, in the case of lymphocytes detection, the accuracies of both AlexNet and LeNet-5 models were 98.96% and 96.78%, respectively. The overall average accuracies of both AlexNet and LeNet-5 models for the whole dataset are 98.58% and 96.32%.

In the case of AlexNet, the accuracy rate in model training starts from 30% and reaches 98.5% at 30 epochs, while LeNet-5 accuracy begins at 30% and achieves 96.32%. Similarly, both models' Quadratic Loss was nearly equal to zero at the 5800th iteration and 30 epochs. The performance compression of both models in Accuracy and Quadratic Loss is shown in Figures 4 and 5.

Based on the results, the overall performance of the AlexNet-based model is found to be satisfactory compared to LeNet-5-based model in terms of Precision, Recall, and Accuracy. Moreover, the Quadratic Loss of the AlexNet-based model decreased with each iteration and reached almost zero at the 5800th iteration. Based on the models'

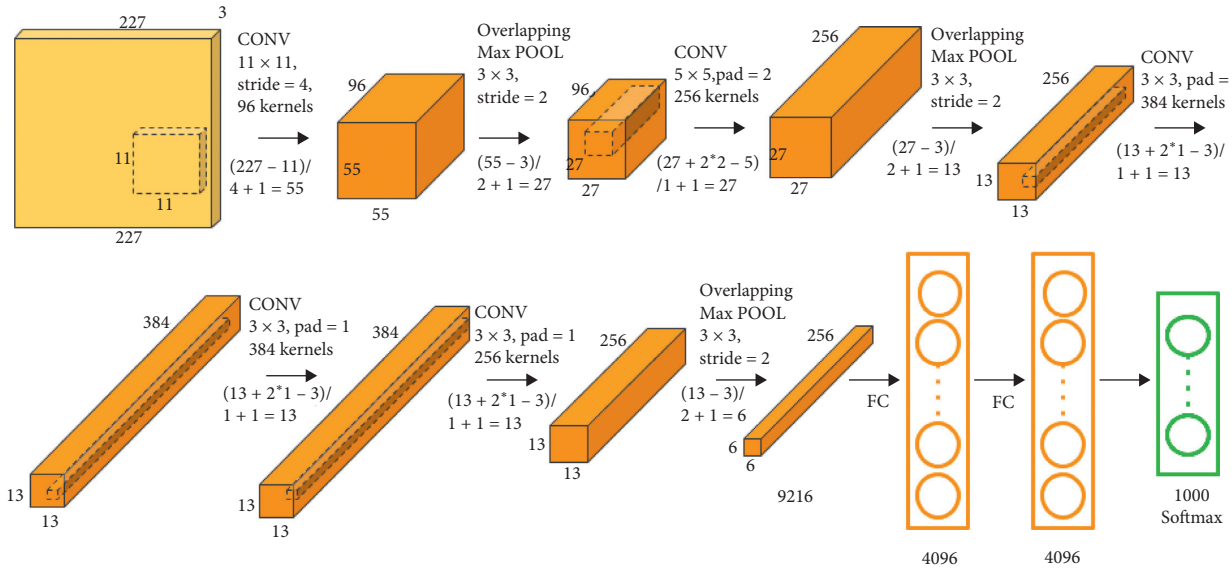

Figure 1: Structure of AlexNet model [12].

Table 2: Parameters detail of AlexNet model.

Algorithm	AlexNet
Maximum number of epochs	30
Convolutional layers	ReLU activation function
Number of iterations	5580
Fully Connected layers	SoftMax activation function
Dataset	4000 images
Training data	70%
Testing data	30%

Table 3: Performance comparison of both LeNet-5- and AlexNet-based models in Precision, Recall, and F-Measure.

Model	Precision	Recall	F-Measure
LeNet-5	0.836	0.853	0.844
AlexNet	0.874	0.889	0.881

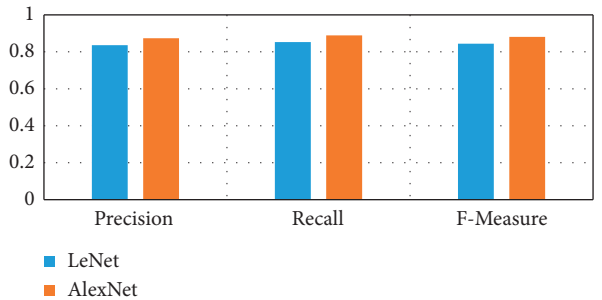

Figure 2: Performance comparison of both LeNet-5- and AlexNet-based models in Precision, Recall, and F-Measure.

Table 4: Performance comparison of both LeNet-5- and AlexNet-based models in terms of Accuracy in each class.

	Normal monocytes	Abnormal monocytes	Lymphocytes	Average
LeNet-5	0.9669	0.9549	0.9678	0.9632
AlexNet	0.9888	0.979	0.9896	0.9858

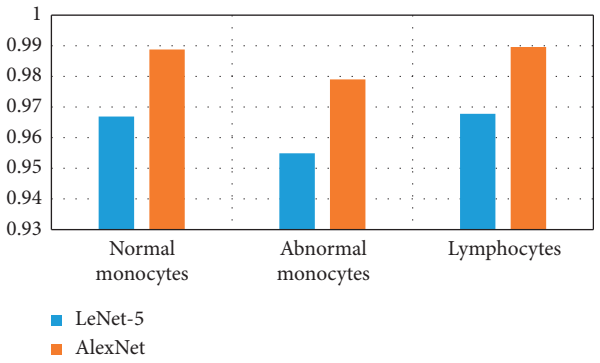

Figure 3: Performance comparison of both LeNet-5- and AlexNet-based models in terms of Accuracy in each class.

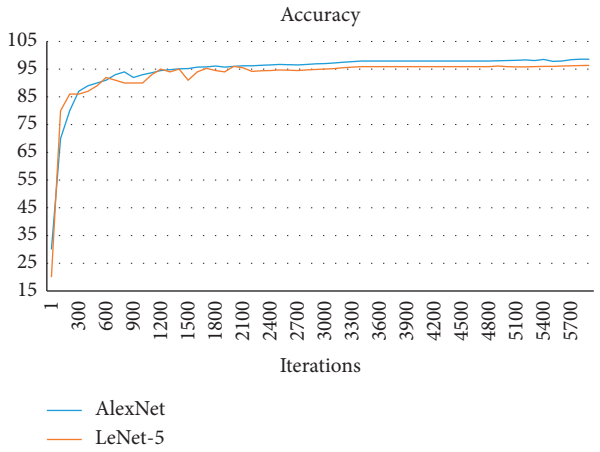

Figure 4: Performance comparison of both LeNet-5- and AlexNet-based models in Accuracy at every iteration.

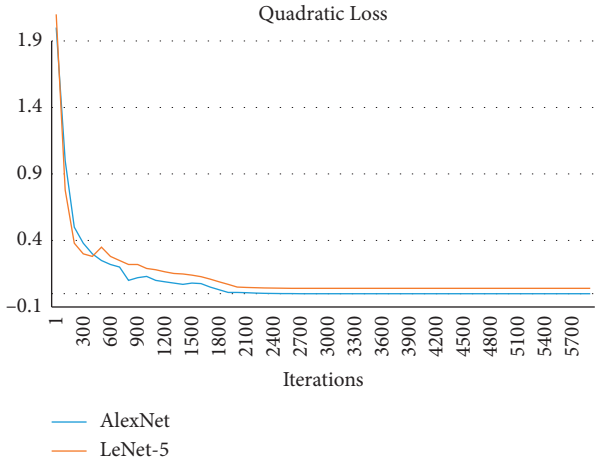

Figure 5: Performance comparison of both LeNet-5- and AlexNet-based models in Quadratic Loss at every iteration.

performance, it is safe to conclude that AlexNet-based models can be effectively used for hematological image analysis and AML detection.

5. Conclusions and Future Work

Acute Myeloid Leukemia (AML) is a hematological disorder and type of cancer that weakens the human immune system by generating malignant WBCs. In this work, we have proposed the AlexNet-based model to identify AML in microscopic blood images and compared its performance with the LeNet-5-based model in Precision, Recall, Accuracy, and Quadratic Loss. LeNet-5 model is composed of two convolutional, two maximum pooling, and three FC layers. In contrast, the AlexNet model has five convolutional, three maximum pooling, and three FC layers. Based on results, it is concluded that AlexNet performed well with high accuracy compared to LeNet-5-based model. AlexNet was able to classify 88.9% images correctly with 87.4% precision and 98.58% accuracy, whereas LeNet-5 correctly identified 85.3% images with 83.6% precision and 96.25% accuracy.

AlexNet algorithm is a competent and well-known deep learning algorithm that can be used efficiently in significant research areas, especially medical image processing. AlexNet can analyze and detect important features from different medical images such as CT scans, X-rays, MRI, PET, ultrasound, and hematological images. In the future, we are planning to apply the AlexNet architecture for other types of leukemia cell detection, such as Acute Lymphatic Leukemia (ALL), to get high accuracy.

Data Availability

The data used to support the findings of this study are available at https://data.mendeley.com/datasets/snkd93bnjr/1.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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