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Detection of brain tumor with a pre-trained deep learning model based on feature selection using MR images

MR görüntüleri kullanılarak öznitelik seçimine dayalı ön-eğitilmiş bir derin öğrenme modeliyle beyin tümörünün tespiti

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Abstract

One of the most dangerous diseases in the world is a brain tumor. A brain tumor destroys healthy tissue in the brain and then multiplies abnormally, causing increased internal pressure in the skull. This can lead to death if not diagnosed early. Magnetic Resonance Imaging (MRI) is a diagnostic method that is frequently used in soft tissues and gives successful results. In this study, a brain tumor was automatically detected from MR images. For feature extraction, a pre-trained Convolutional Neural Network (CNN) model named MobilenetV2 was used. Then, the ReliefF algorithm was used for feature selection. The features extracted with MobileNetV2 and the features selected with the ReliefF algorithm are given separately to the classifiers and the system performance is tested. As a result of experimental studies, it was seen that the highest performance was obtained with the combination of MobileNetV2 feature extraction, ReliefF algorithm feature selection, and KNN classifier.

Keywords: Feature selection, ReliefF algorithm, MobileNetV2, brain tumor, Magnetic resonance imaging

Özet

Dünyadaki en tehlikeli hastalıklardan biri beyin tümörüdür. Bir beyin tümörü beyindeki sağlıklı dokuyu yok eder ve daha sonra anormal şekilde çoğalarak kafatasında iç basıncın artmasına neden olur. Bu erken teşhis edilmezse ölüme yol açabilir. Manyetik Rezonans Görüntüleme (MRG) yumuşak dokularda sıklıkla kullanılan ve başarılı sonuçlar veren bir tanı yöntemidir. Bu çalışmada, MR görüntülerinden bir beyin tümörü otomatik olarak tespit edildi. Öznitelik çıkarımı için MobilenetV2 adlı önceden eğitilmiş bir Evrişimsel Sinir Ağı modeli kullanılmıştır. Daha sonra öznitelik seçimi için ReliefF algoritması kullanılmıştır. MobileNetV2 ile çıkarılan öznitelikler ve ReliefF algoritması ile seçilen öznitelikler ayrı ayrı sınıflandırıcılara verilerek sistem performansı test edilmiştir. Deneysel çalışmalar sonucu MobileNetV2 öznitelik çıkarımı, ReliefF algoritması öznitelik seçimi ve KNN sınıflandırıcı kombinasyonuyla en yüksek başarımın elde edildiği görülmüştür.

Anahtar kelimeler: Öznitelik seçimi, ReliefF algoritması, MobileNetV2, Beyin tümörü, Manyetik rezonans görüntüleri

1. Introduction

The brain is one of the body's most intricate organs. A brain tumor is a clump of tissue that develops and multiplies uncontrolled in the brain [1]. The American Society of Clinical Oncology estimates that between 85.0% and 90% of the brain, cancers are malignancies of the central nervous system [2]. Despite being less frequent than other tumor forms in the central nervous system, brain tumors in particular have a high death rate. Therefore, the efficacy of treatment and the reduction of mortality from brain tumors depend greatly on early identification [3].

MRI is superior to other imaging methods like computed tomography (CT) and positron emission tomography in several ways (PET). Magnetic resonance imaging (MRI) technologies offer researchers more detailed, increased contrast images of the brain for the detection of brain malignancies. Additionally, MRI is a non-invasive method that is safe for the human

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body. Additionally, MRI technology is quick and takes less time to finish treatments. Consequently, MRI has emerged as the method of choice in clinical practice for finding brain tumors [4].

The use of clinical information and qualified radiologists and other specialists is essential for the early diagnosis of brain tumors. Decision-making processes for the detection of brain tumors might be time-consuming due to the shortage of professionals in healthcare. Computer-aided systems powered by artificial intelligence can lessen professionals' workloads and help them make decisions [4,5].

Traditional approaches could work well for one dataset but poorly for another since the right features must be extracted for each data format. Convolution filters found in deep learning architectures eliminate the requirement for manual feature extraction. Because of this, deep learning-based studies have excelled at several tasks involving the classification of medical images [6–20]. A pre-trained CNN-based model was utilized by Lu et al. [21] to identify brain cancers in MRI images. The MobileNetV2 model's deep features were extracted. The random vector functional-network approach had a classification accuracy of 96.0%. The binary classification had a classification accuracy of over 95.0%. For brain MRI classification, Talo et al. [22] used five pre-trained CNN networks, including AlexNet, VGG16, ResNet (18, 34, and 50) models. ResNet50 had the best accuracy, 95.23%. A unique strategy for brain MRI categorization including various processes was reported by Kumar and Mankame [23]. For segmentation, a combination fuzzy structure and a sine-cosine algorithm were employed. The segmented images were then utilized to extract features using a statistical method and a local binary model (LBP). In order to categorize data, a deep CNN model that was built from scratch was used. The method's highest degree of accuracy was 96.23%.

To identify the two types of brain tumors that fall under the deep autoencoder model, low- and high-grade gliomas, Raja and Siva [24] developed an architecture. First, a median filter was used to preprocess MR images. Second, segmentation was accomplished using a Bayesian clustering approach. An end-to-end learning deep autoencoder model was used to classify the MR image samples. The approach had a 98.5% accuracy rate. A unique CNN model was chosen by Devi and Gomathi [25] for automatic brain tumor identification. For preprocessing, a canny edge detection technique was applied. Then, MR sample saliency map representations were created. A CNN model with five convolutional layers was used for the prediction procedure, yielding 91.0% accuracy. For the 3-class (glioma, meningioma, and pituitary tumor) brain MRI classification, Alhassan and Zainon [26] suggested a deep CNN structure based on a hard swish-based ReLU activation function. The classification performance was enhanced by 3.5% accuracy thanks to the hard swish-based ReLU activation function, with the highest accuracy being 98.26%. For the classification of brain tumors, Kumar et al. [27] used a ResNet50-based method that included the glioma, meningioma, and pituitary classifications. The accuracy results were 97.48% and 97.08%, respectively, with and without data augmentation. A unique method for classifying brain tumors into three categories was devised by Kokkala et al. [128]. To identify glioma, meningioma, and pituitary samples, a deep dense initial residual network was trained. The model had a 99.26% average accuracy. A unique strategy for 2-class brain MR image categorization was put forth by Mesut et al. [29]. In this method, deep feature extraction was carried out using two pre-trained CNN models, VGG16 and AlexNet. Moreover, all CNN models' convolutional layers were subjected to the Hypercolumn method. As a result, the deep feature set now includes local discriminative features. Out of the 2000 features collected, 200 features with good representativeness were chosen using the recursive feature elimination (RFE) algorithm. The SVM classifier's greatest accuracy was 96.77%. A strategy based on deep feature extraction was put out by Kang et al. [30] for the classification of 4-class brain MRI images. Popular pre-trained CNN models like ResNet, DenseNet-169, VGGNet, AlexNet, Inceptionv3, ResNeXt, ShuffleNet, MobileNetV2, and MnasNet were used to extract deep features. In order to achieve the best feature performance, DenseNet-169, ShuffleNet, and MnasNet models were combined. Several classifier techniques, including Adaboost, Gaussian Naive Bayes, K-Nearest Neighbor (KNN), Random Forest, and Support Vector Machine (SVM), were utilized in the classification phase. The SVM classifier produced the best classification results. 93.72% accuracy was the highest. A novel method for tumor detection and tumor classification from brain MR images was developed by Arı et al. [31]. First, a Gaussian filter is used to preprocess MR images of the brain. Then, using the proper threshold and morphological operations, malignancies were found. Different combinations of deep features were recovered from the fc6 and fc7 layers of the AlexNet and VGG16 models. In the classification phase, ELM was utilized. On three datasets, the proposed method's effectiveness was evaluated.

2. Preliminaries

Classifiers

The Linear discriminant (LD) method is frequently used in both classification and feature reduction. LD assumes that each class produces different Gaussian distributions. LD then finds the best decomposition by considering the maximum variance between classes [32]. SVM is a commonly used supervised machine learning method. The main idea behind SVM is Vapnik's statistical learning theory. SVM projects the input data into higher dimensional space and builds the hyperplane to separate classes in the projected space. Basically, SVM solves linear problems. For solving nonlinear problems, SVM uses nonlinear kernel functions such as Gaussian, sigmoid, and polynomial [33]. KNN is a fundamental and widely used supervised machine learning technique. KNN uses local knowledge of the predicted input data, so it is a feasible and adaptive method. KNN solves the problem by considering the input data point neighbor relations. KNN uses distance metrics such as Euclidean, Minkowski, Manhattan, Manhattan, Cosine, Hamming, etc. to detect the neighborhood relationship. The k closest instances are selected from the input data, then any class is assigned according to the majority relations. The number of neighbors, k, should be an odd number to avoid ambiguity [34]. Decision Trees (DT) are a tree-based algorithm used in classification and regression problems and are one of the most widely used predictive methods. Each node in the tree represents a test on a feature. Node branches indicate the result of the test. Tree leaves contain the class labels. Decision tree inference consists of tree construction and tree cleaning phases [35].

MobileNetV2

Sandler [36] has suggested MobileNetV2, a CNN architecture for mobile devices. The initial version, which was created for face feature detection, was tested and trained using data from Google [37]. An inverted residual and a linear bottleneck are used in the network structure that was created. It is intended for generic feature extraction as well as image categorization. This network implements bottleneck operations, mean pooling, 3×3 and 1×1 convolution. Layers in MobileNetV2 total 154. Compared to other popular CNN models, MobileNetV2 employs fewer parameters [38]. An effective network design with rapid execution is MobileNetV2. Figure 1 displays the MobileNetV2 convolutional blocks.

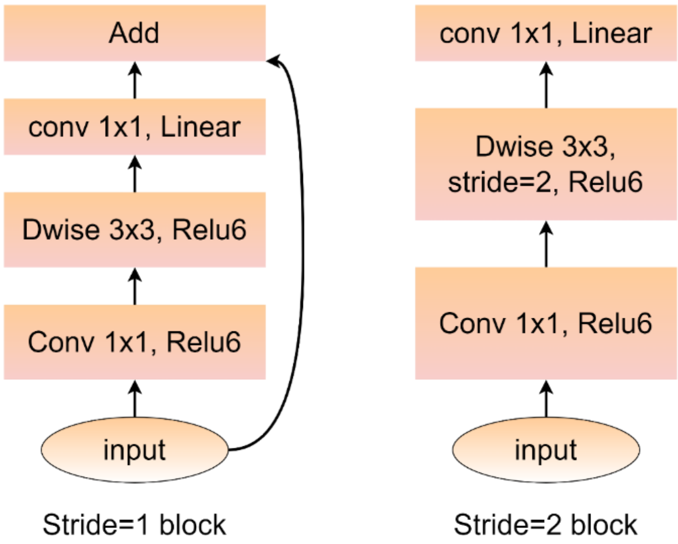

Figure 1. MobileNetV2 convolutional blocks

Relief family of algorithm

Kira and Rendell developed the Relief algorithm in 1992, which is highly sensitive to feature interactions and uses a filter-method approach to feature selection [39]. It was initially intended for use in discrete or numerical feature binary classification issues. Each feature in Relief has a feature score, which may be used to rank and select the features with the highest scores. Further modeling can be guided by these scores, which can also serve as feature weights. Relief feature scoring is built on the identification of feature value differences between nearest neighbor instance pairs. If a close instance pair of the same class exhibits a variation in feature value, the feature score is reduced (a "hit"). As an alternative, the feature score increases if a neighboring instance pair with a different class value exhibits a feature value difference (a "miss") [40].

3. Method

The framework of the proposed approach is given in Figure 2. In this study, a novel approach for automatic ophthalmologic disease detection from MR images is proposed. In the first step, deep features are extracted from the pre-trained MobileNetV2 ESA model. In the second step, discriminative features are selected using a multi-level algorithm with INCA algorithms[41-43]. This algorithm improves the classification performance and reduces the computational cost of the classifier. At the third level, the selected features are passed to the SVM classifier.

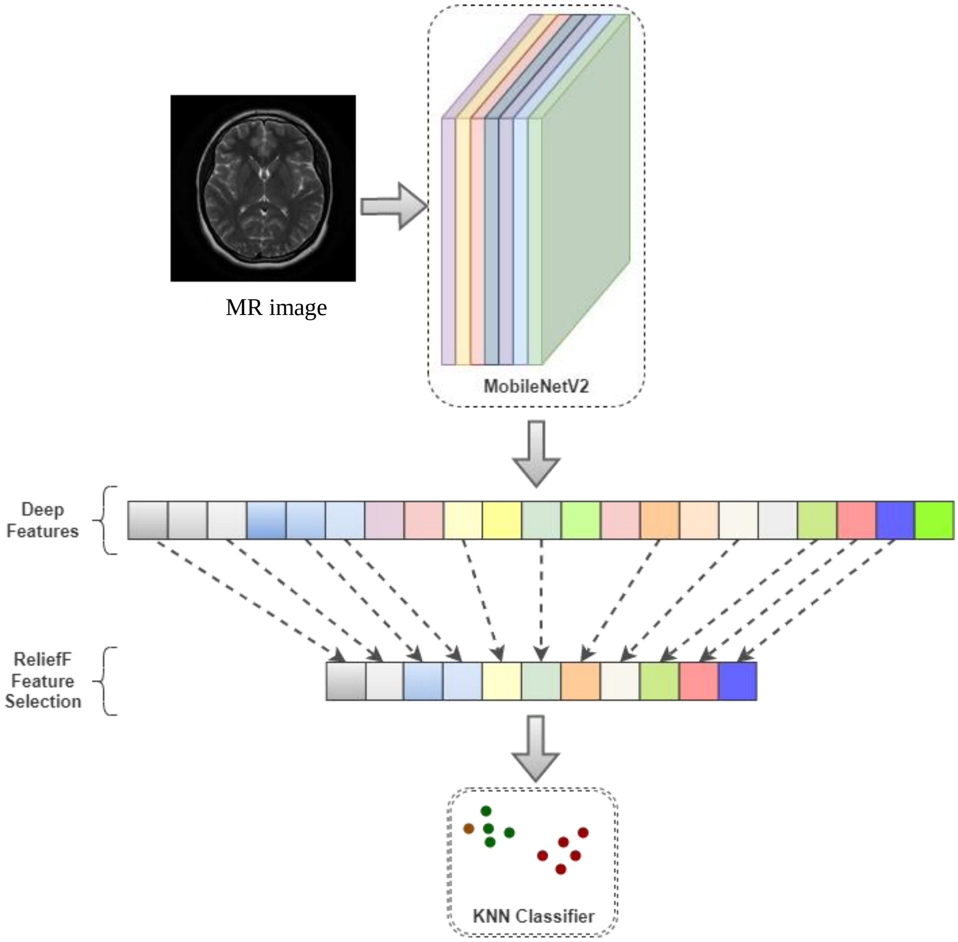

Figure 2. Proposed approach architecture

4. Experiments and discussion

On a dataset that is available to the public, the suggested approach was assessed. The collection included MR pictures of both brain tumors and healthy individuals [44]. 155 cases of brain tumors and 98 cases of healthy tissue resulted in the collection of 253 MR images. The MR pictures were stored in JPEG format with various resolutions and size settings. The dataset examples are provided in Figure 3.

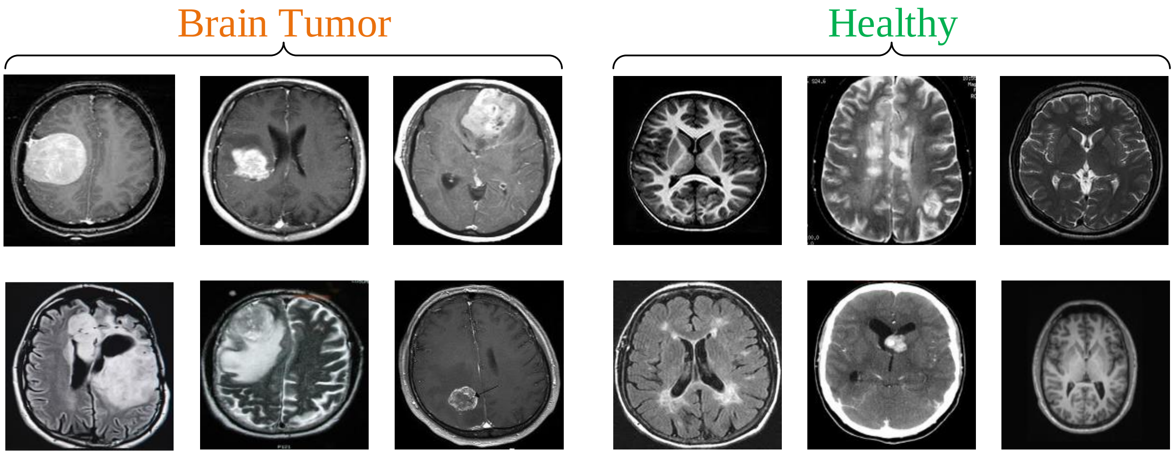

Figure 3. Samples for each class on the datasets

The study's entire coding was carried out using Matlab software. The PC used in the study has 16 GB of main memory, an Intel i5 processor, and a 4 GB video card. A fully connected layer of the MobileNetV2 ESA model called "Logits" was utilized for the extraction of deep features, and 1000 deep features were recovered from it. After that, the ReliefF feature selection technique was applied to boost classification performance while lowering computing costs. The number of nearest neighbors, a crucial parameter in this technique, was set at 10. Figure 4 provides a representation of the feature weights computed using this technique.

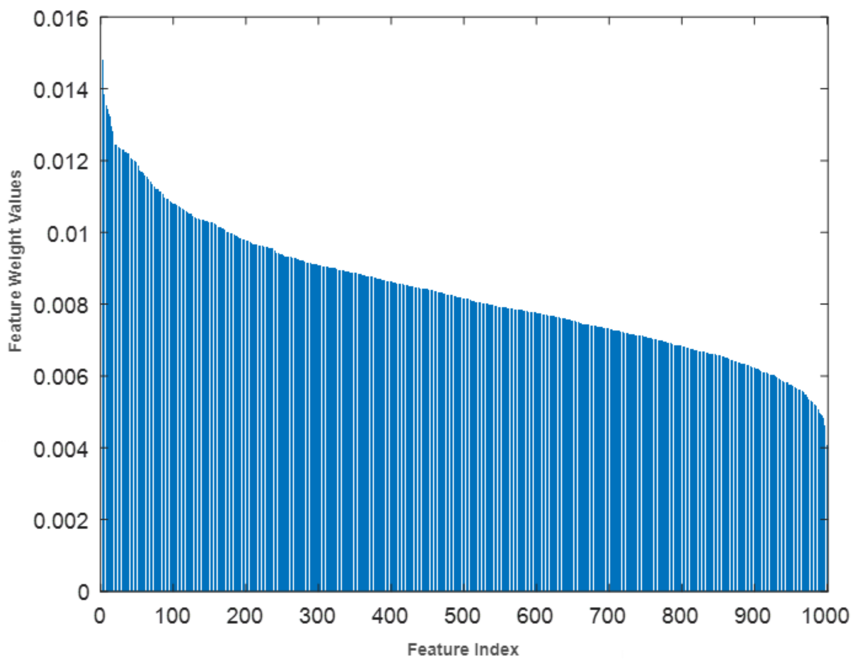

Figure 4. Feature weights calculated with the ReliefF algorithm

The weight values of these computed attributes were used to choose the first 300 attributes. The Matlab Classification Learner tool received these features for classification. The evaluation method was 10-fold cross-validation. This procedure was repeated twice, once before feature selection and once after. Table 1 provides the categorization accuracy results from this technique.

Table 1. Classification performance

Classifier	All features	Selected features (with ReliefF)
DT	0.88	0.91
LD	0.86	0.90
SVM	0.92	0.94
KNN	**0.95**	**0.99**

As shown in Table 1, the ReliefF feature selection algorithm improved the performance of all classifiers. The best classification performance was obtained with the KNN algorithm (0.99).

The complexity matrices in Figure 5 are given to see the effect of feature selection on classification performance. As demonstrated above, the ReliefF algorithm increased the number of predicted instances in both classes and as a result, the accuracy was improved by 4%.

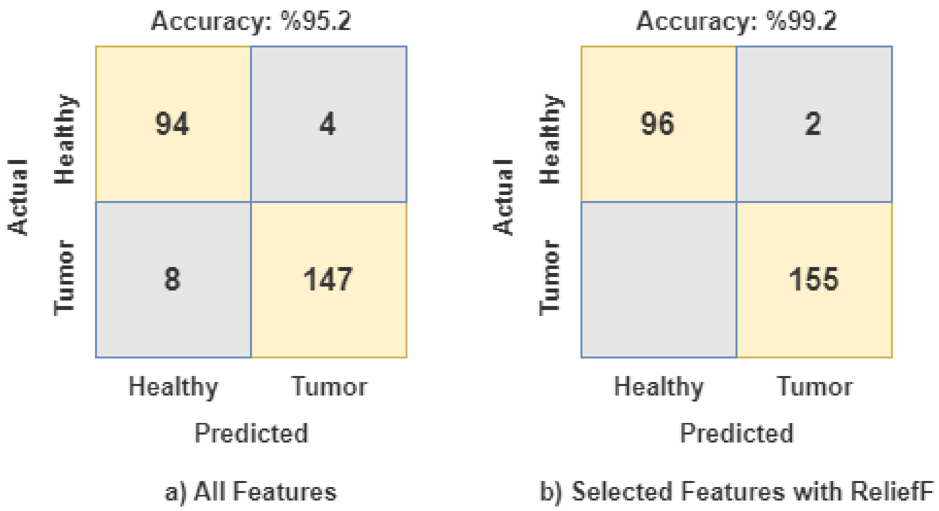

Figure 5. ReliefF impact of feature selection on performance

When the studies conducted with the same data are examined, Table 2 presents the general summary. Nanda et al. [45] emphasized that they used a new hybrid saliency k-mean segmentation (Saliency-K-mean-SSO-RBNN) by taking advantage of the social spider optimization (SSO) algorithm in their study in the Radial Basis Neural Network (RBNN). The salience map focuses on the relevant point in the target image. It was reported that 96%, 92%, and 94% accuracy were obtained in the study, in which processes were tested with three different data sets. Demir and Akbulut [46], used the convolution and fully connected layers of a new R-CNN model in the deep feature extraction phase. Among the features obtained, the 100 most dominant features in terms of distinctiveness were selected with the L1NSR algorithm. The best performance in the classification phase was obtained with SVM using the Gaussian kernel. In addition, in the study, the method was tested with another data set with four classes and 96.6% accuracy was achieved. Alnabhan et al. [47] wanted to reduce the complex relationship of CNN parameters by using Egyptian Vulture Optimization (EVO) technique in their study. They also tested their methods, which they tested with ANN and deep learning-based classifiers, on another data set with four classes. Asif et al. [48], tested their proposed method with two different data sets in their study. Preprocessed MR images were exported to Xception, NasNet Large, DenseNet121, and InceptionResNetV2. They used ADAM, SGD, and RMSprop algorithms as optimizers when using MR images for testing. They obtained 99.67% accuracy by using the Xception model with the data set having a larger sample size.

Table 2. Comparison of current studies with the same data set [43]

Reference	Method	Classification	(Acc.%)
Nanda et al. (2023)	Saliency-K-mean-SSO	RBNN	%92
Demir and Akbulut (2022)	R-CNN, L1NSR	SVM	%98.8
Alnabhan et al. (2022)	CNN-based EVO model	CNN	%93.51
Asif et al. (2022)	Xception, ADAM optimization	Xception	%91.94
Proposed Method	**MobileNetV2, ReliefF algorithm**	**KNN**	**%99**

5. Conclusion

In this study, a deep learning-based hybrid technique for the classification of brain tumors is presented. In the study, deep features were extracted with the pre-trained MobileNetV2 architecture. It is desired to reduce the computational cost and processing load without transmitting the features to the KNN algorithm, which is a powerful classifier. The ReliefF algorithm is used for the mentioned feature extraction step. In order to see the performance effect of the algorithm on the designed model, the model in which all the features are added to the system and the situation after the feature selection is given to the classifier separately. As a result of the comparison, it was concluded that the classification performed 2% better, and ultimately a high accuracy of 99% was achieved. The mentioned success rate can be a helpful system for experts since the treatment and diagnosis stage of brain tumors is considered to be of critical importance. In future studies, it is planned to test CNN models trained from scratch on the same dataset to improve classification accuracy.

6. Acknowledgements

We would like to thank the researcher for providing a publicly available dataset [44].

7. Author Contribution Statement

All the authors in this research made one or two contributions toward the success of this research. Author 1, provided the finite element solution of the diffusivity equation while Author 2 used the result from the first author to analyze the reservoir production rate and cumulative production. Authors 2 and 3 supervised the research and help in the validation of the result using relevant literature.

8. Ethics Committee Approval and Conflict of Interest

There is no need for an ethics committee approval in the prepared article and there is no conflict of interest with any person/institution in the prepared article.

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