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ÖNSÖZ/FOREWORD

Çok değerli Bilişim Kongresi katılımcıları,

Bilgi çağının dönüşüm dinamikleri, bireylerden kurumlara kadar tüm yapıları yeniden şekillendirmektedir. Dijitalleşmenin toplumsal, ekonomik ve akademik hayat üzerindeki etkileri her geçen gün artarken; üniversiteler, bu sürecin bilgi üretimi ve yayılımı açısından temel aktörleri arasında yer almaktadır. Batman Üniversitesi olarak bizler de bu bilinçle, bilimsel etkinlikleri desteklemeyi ve ulusal-uluslararası iş birliklerini teşvik etmeyi öncelikli misyonumuz olarak görmekteyiz.

Bu doğrultuda düzenlediğimiz IV. Uluslararası Bilişim Kongresi (IIC2025), akademik çevreler ile sektör temsilcilerini aynı platformda buluşturarak, güncel teknolojik gelişmelerin çok yönlü tartışılmasına olanak tanımıştır. Kongremiz kapsamında yapay zekâ, kuantum ile blokzincir teknolojileri, veri madenciliği ve siber güvenlik gibi bilişim teknolojilerinin öncelikli alanlarında sunulan bildiriler, bilişim ekosistemine önemli katkılar sağlamıştır.

Ayrıca kongre süresince gerçekleştirilen açılış oturumları, tematik paneller ve ödül törenleri, etkinliğin yalnızca akademik değil, sosyal ve kültürel açıdan da zenginleşmesine katkıda bulunmuştur.

Kongremizin gerçekleştirilmesinde emeği geçen düzenleme ve bilim kurulu üyelerine, bildirileriyle katkı sunan araştırmacılara, desteklerini esirgemeyen tüm kurum ve kuruluşlara teşekkür ediyor; gelecek organizasyonlarda tekrar buluşmayı temenni ediyorum.

Prof. Dr. İdris DEMİR
Onursal Başkan
Batman Üniversitesi Rektörü

Tam Metin Bildiriler Bölümü

Full Text Papers Section

DL MODELS AND THEIR EVALUATION IN SCOLIOSIS DIAGNOSIS

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***Abstract:** This study employs advanced AI techniques, including DenseNet121, ViT-B16, EfficientNet-B0, ResNet50, and ConvNeXt, to diagnose scoliosis non-invasively without radiation exposure. The research employs a specialized dataset composed of back surface images, which are categorized into two primary classes: "scoliosis present" and "scoliosis absent." The models were trained using the PyTorch framework, and the dataset was enhanced through various data augmentation techniques. The models' performances were compared in terms of accuracy, sensitivity, specificity, and AUC metrics. The models used in this study achieved accuracy levels comparable to those of clinical experts, offering a potential alternative for scoliosis screening applications. The findings indicate that analysis based on back surface images can serve as an effective method for scoliosis diagnosis. Furthermore, the study suggests that this low-cost, easily applicable, and radiation-free approach could be feasibly implemented in community-based scoliosis screening programs.*

***Keywords**: Scoliosis Diagnosis, DL Models, Radiation-Free Detection, Machine Learning*

1. INTRODUCTION

Scoliosis is an abnormal curvature of the spine that usually begins at a young age and can lead to serious health problems if left untreated. Adolescent idiopathic scoliosis (AIS) is defined as a curvature of the spine of 10° or more of unknown etiology in people aged 10 to 18 years. [1]. It is the most common spinal disorder among adolescents, affecting 0.5–5.2% worldwide. Scoliosis usually presents as a deformity of the back, more rarely found by chance on radiography or associated with complaints of pain or unrelated symptoms. Trunk instability and asymmetrical rib protrusion, also known as "rib hump," often accompany the curve [2], [3].

Early diagnosis not only enhances the effectiveness of the treatment process but also prevents the progression of scoliosis. Today, scoliosis is mostly diagnosed by physical examination and radiologic imaging. [4] However, traditional radiologic methods, such as X-rays, expose patients to high doses of radiation, especially children and adolescents, posing long-term health risks. For this reason, the need for radiation-free, non-invasive methods is increasing day by day. In this context, the use of DL techniques in medical imaging recently has enabled the development of safer and more effective diagnostic methods [5]

DL models are revolutionizing the field of medical image analysis, especially with their ability to process large data sets and high accuracy [6], [7], [8].

Early detection of health problems such as scoliosis has become easier thanks to the success of DL techniques in medical images [9], [10] This study aims to automatically detect scoliosis on back surface images. The use of back surface images enables fast and low-cost screening of patients without radiation exposure. Thus, scoliosis detection will enable healthcare services to reach a wider audience and become more socially effective and widespread. Traditional scoliosis screening methods are readily available but require referral and radiographic exposure due to low positive predictive values. The use of AI and DL algorithms has the potential to reduce unnecessary referrals and scoliosis screening costs, for instance, scoliosis screening costs [11], [12]. Recent case studies demonstrate that unusual clinical presentations can significantly complicate accurate diagnoses and timely referrals. Integrating DL-based approaches into routine screening could therefore enhance diagnostic clarity, especially in identifying uncommon or extraordinary anatomical presentations early [10], [12], [13]. There are many ML-based studies in the literature using back images and other non-invasive methods for scoliosis diagnosis. These methods have been developed specifically to reduce radiation exposure and provide safer alternatives for repeat follow-up. We summarize some of these methods in Table 1.

Table 1. *Comparison of ML-Based Approach*

Referans, year	ML Method(s)	Dataset(s)	Results (%)
Yang, J., et al. [14], 2019	ResNet-101	Back images from institutions in China	75.0% (scoliosis detection, curve ≥10°)
Kokabu, T., et al. [15], 2021	CNN	3D depth sensor images	94% (for Cobb angle ≥10°)
He et al. [16], 2024	Swin-pix2pix (conditional GAN)	Smartphone photos	93% (diagnostic accuracy for the master curve)
Duan et al. [17], 2025	Dual AttentionUNet	Back surface images	AUC: 0,927 (for classification)
Li et al. [18], 2024	YOLOv8	Back photos taken with a mobile phone	70.2% (clinical validation)
Proposed method, 2025	DenseNet121, ResNet50, EfficientNet-B0, ViT-B16, ConvNeXt-Tiny	Scoliosis Images Collected from Kaggle	%88 (DenseNet121)

Yang et al. [14] trained the ResNet-101 model with back images from three centers in China and reported 75% accuracy in detecting scoliosis cases. Kokabu et al. [15]achieved 94% accuracy with a CNN-based model developed over 3D depth sensor images. although this method is different from 2D images, it offers a meaningful comparison in scoliosis classification. Another study using Swin-pix2pix architecture reported 93% accuracy for scoliosis diagnosis from back photos taken with a smartphone [16]. Similarly, in a study using the Dual AttentionUNet model, was reported with back surface images, indicating classification success [17]. On the other hand, in a YOLOv8-based study, 70.2% accuracy was obtained with mobile images; although this rate was relatively low, it was found to be comparable in terms of the type of data used [18].

In our study, we looked at how well five different DL models performed: ResNet50, DenseNet121, EfficientNet-B0, ViT-B16, and ConvNeXt-Tiny. These models represent a new generation of approaches based on both CNN [19] and Transformer. ResNet50 is a model that optimizes the connections between layers, widely used in deep learning [20]. DenseNet121 has a structure that enables more efficient learning through feature sharing. [21]. EfficientNet-B0 stands out as a model that offers high accuracy with lower computational cost [22]. ConvNeXt can provide high accuracy, especially in natural image processing tasks [23]. ViT offers an alternative approach to traditional CNN models by processing visual data with transformer structures. [24]. Recent studies indicate that DL-based models can significantly enhance diagnostic accuracy in complex tumor cases involving soft tissue and bone structures. Our findings also suggest that integrating transformer-based architectures, like ViT, can be particularly advantageous in scenarios where tumor boundaries and invasion pathways are challenging to delineate precisely [25]

We trained these models using the PyTorch framework and expanded the limited dataset through data augmentation technique. We analyzed each model's performance in detail using metrics like accuracy, loss, and ROC curve during this process. The results indicate that the models used can achieve high accuracy rates in scoliosis detection with bare back images and that these methods offer a potential alternative for medical scans. This study demonstrates that DL can be effectively applied in the field of medical imaging and that radiation-free, low-cost, and easy-to-implement solutions can be used throughout society. These findings could be an important step toward making scoliosis screenings more widely available and facilitating early diagnosis.

2. MATERIALS AND METHODS

Various DL models have been used for the automatic detection of scoliosis [4], [10], [26]. This study aims to provide a low-cost, radiation-free, and non-invasive screening method for back surface images. The DL models used in the research are DenseNet121, ResNet50, EfficientNet-B0, ViT-B16, and ConvNeXt-Tiny. Traditional diagnostic tools for scoliosis screening require a significant number of specialized personnel and hardware, which causes discomfort that can lead to missed opportunities for early diagnosis and optimal treatment. We developed an image segmentation model based on DL to improve the efficiency of scoliosis screening.

We conducted the scoliosis diagnosis using a dataset obtained from Kaggle [27] , comprising various patient images. The dataset consists of bare back images labeled as “scoliosis present” and “scoliosis absent” and divided into two main classes. We divide the dataset into three main parts: training, validation, and testing, with an equal number of images for each class. The dataset was hosted on Google Drive and processed with the PyTorch framework. We applied data augmentation methods to the limited data size to enhance the model's generalization capability. The augmentation techniques used include random rotation, color change, horizontal rotation, and random cropping. This approach reduced the risk of overfitting and provided a more robust training process.

Each model was trained with the PyTorch framework. We trained the models using the cross-entropy loss function and optimized them using the Adam optimization algorithm. Each model was trained using a GPU, with performance monitored via accuracy, loss, and ROC curve metrics (Receiver Operating Characteristic curve). Throughout the training process, the accuracy and AUC of each model were calculated in detail, and the results were compared. The training process continued for 20 epochs (Table 2).

Table 2. *Model architecture details*

Training rate	Batch size	Optimization algorithm	Performance indicators	Loss function	Number of epochs	Re-scaling
1e-3	64	Adam	accuracy	Categorical crossentopy	30	1/.255

2.1. DL Models Used and Their Contributions in Scoliosis Diagnosis

This study compares different DL architectures for automating scoliosis diagnosis. The selected models include modern approaches based on CNN and Visual Transformer Therefore, we evaluate the performance of both classical and next-generation architectures.

2.1.1. DenseNet121

The DenseNet121 model is a convolutional neural network that enriches the flow of information by establishing dense connections between layers. In this architecture, each layer takes as input the outputs from all previous layers. DenseNet121 is able to overcome the vanishing gradient problem, thus allowing the creation of networks of sufficient depth, but the network has fewer parameters than other networks, making it fast. This feature was useful in cases where structural defects such as scoliosis are detected with small details on the image, allowing the model to learn in depth without losing details [28].

2.1.2. ResNet50

ResNet50 is a 50-layer deep network that avoids the problem of gradient fading despite increasing depth thanks to "residual connections." Trained on the ImageNet dataset For ResNet 50 networks, we can easily download weights and modify the final layers to quickly generate models to address new problems[29]. It can detect scoliosis with balanced performance by capturing both local and global structural changes that impact spinal curvature at the same time.

2.1.3 EfficientNet-B0

The EfficientNet architecture aims to achieve an optimal balance between model size and accuracy. EfficientNet-B0 is the base architecture in the EfficientNet family, utilizing MBConv blocks enhanced by Squeeze-and-Excitation (SE) modules. Unlike its scaled variants (B1-B7), EfficientNet-B0 serves as the foundational model upon which compound scaling techniques-simultaneously adjusting depth, width, and resolution—are applied to develop larger models. Due to its compact structure, EfficientNet-B0 achieves high accuracy with relatively low computational demands [30]. This compactness also contributes to its effectiveness in preventing overfitting, making it especially suitable for scoliosis detection tasks involving limited datasets.

2.1.4 ViT-B16

ViT-B16 is an attention mechanism-based model that uses the pure Transformer architecture to analyze visual data. It is particularly powerful in capturing long-range dependencies and effectively learns global patterns in images [31]. For the detection of structural disorders such as scoliosis, this model was included in the study due to its ability to capture global distortions in back images.

2.1.5 ConvNeXt Tiny

ConvNeXtTiny is a next-generation CNN architecture that combines modern convolutional structures with Transformer-like improvements. It takes advantage of both the efficiency of convolutional models and the high accuracy of Transformer-based models [32].

2.2. Data Set and Procedures Applied in the Training/Testing Process

In this study, Kaggle and the "Collected Scoliosis Images" dataset, which contains real patient images, were used [27]. The "Collected Scoliosis Images" dataset contains various images related to scoliosis and provides a valuable resource for researchers in the fields of medical image processing, machine learning, and deep learning. We divide the data into two classes: "Yes" (15) and "No" (20). We performed the following procedures as standard in model training.

2.2.1. Data Splitting

The study divides the dataset into three distinct subsets for model training, validation, and testing. Generally, the data is divided into 70% training, 15% validation, and 15% testing. The training set is used for the learning process of the model, while the validation set is used for hyperparameter adjustments and to prevent overlearning. The test set is reserved to objectively measure the overall performance of the model.

2.2.2. Data Augmentation

Data augmentation is used to increase the generalization ability of the model in limited data sets and to prevent overfitting. We applied transformation and diversification techniques in this study to train the model on a wider variety of samples and stabilize its performance. We applied the following operations to the training dataset:

- Random resizing and cropping
- Horizontal rotation
- Color saturation and brightness variation
- We performed some minor turning and shifting operations.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1 - SCR = \frac{2 * PRE * Recall}{PRE + Recall} \tag{4}$$

In Eq. (1)-(4), TP represents True Positive, TN True Negative, FP False Positive, and FN False Negative. An ROC (Receiver Operating Characteristic) curve shows the relationship between the true positive rate (TPR) and the false positive rate (FPR) of the model. We use this curve to assess the model's discriminative power, particularly in binary classification problems. We calculate the TPR and FPR values using Eq. (5) and Eq. (6), respectively [36]:

$$TPR = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{5}$$

$$FPR = \frac{\mathrm{FP}}{\mathrm{FP} + \mathrm{TN}} \tag{6}$$

3. RESULTS AND DISCUSSION

The DL models used in this study achieved high accuracy rates in the automatic detection of scoliosis on bare back images. The DenseNet121 model showed the best performance with an overall accuracy of 88% and an AUC of 0.98%. The results obtained support the usability of deep learning-based systems in clinical applications as a radiation-free and low-cost screening method. In addition, the success performance of each model of the study is analyzed in detail.

3.1. DenseNet121 Model Metric Outputs

The accuracy and loss graphs illustrate model learning dynamics by visualizing performance changes across training and validation sets. In particular, the early stabilization of the validation accuracy shows that the model adapts quickly on limited data. As can be seen in Fig. 1, the training loss of the DenseNet121 model decreases steadily throughout the training process while the accuracy rate increases.

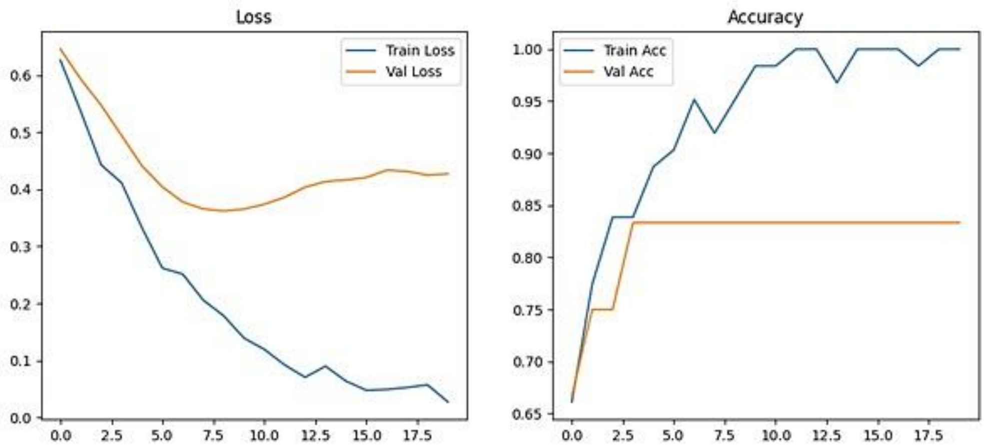


Figure 1. *Accuracy and loss graph for the DenseNet121 model*

In Fig. 1, the steady verification accuracy at the beginning and the changing verification loss shows that the model finishes learning quickly because of limited data and a chance of overlearning. However, overall, the model demonstrated a stable learning performance with high accuracy and low loss values. According to the confusion matrix presented in Fig. 2, the model correctly classified 90% (9/10) of individuals with scoliosis and 83% (5/6) of normal individuals.

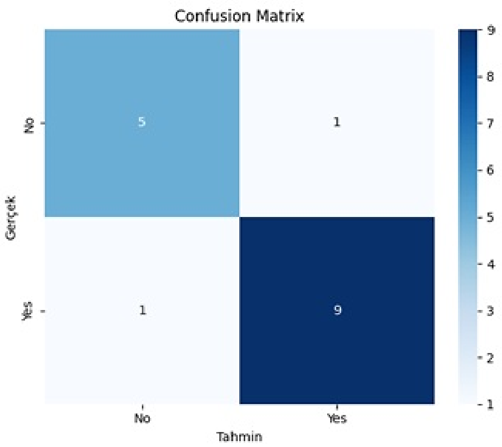


Figure 2. *Confusion matrix of the DenseNet121*

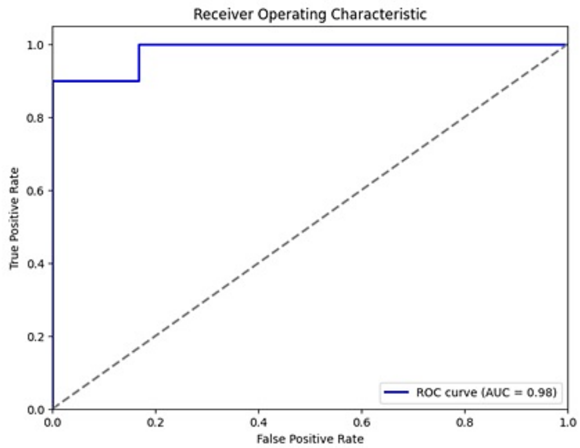


Figure 3. *DenseNet121 ROC Curve*

These results in Fig. 2 show that the model performs with a balanced and high accuracy in both positive and negative classes. The area under the ROC curve (AUC) value shown in the Fig. is 0.98. This high AUC value indicates that the model can classify scoliotic and normal individuals with a very high degree of discrimination and can be used as a reliable diagnostic tool in clinical applications. Table 3 presents the general person metrics of our DenseNet121 model in our study.

Table 3. *Classification Performance Metrics for the DenseNet121 Model*

Class	Precision	Recall	F1-Score	Support
No	0.83	0.83	0.83	6
Yes	0.9	0.9	0.9	10
Accuracy			0.88	16
Macro Avg	0.87	0.87	0.87	16
Weighted Avg	0.88	0.88	0.88	16

Table 2 shows that the overall accuracy of the model is 88%, and the precision, recall, and F1-score values for the positive class (individuals with scoliosis) are 0.90. This value indicates that the model achieves balanced classification performance and demonstrates high reliability in diagnosing scoliosis. Furthermore, the model consistently produces results, unaffected by class imbalance, as indicated by the high values of macro and weighted means.

3.2. ViT-B_16 Model Metric Outputs

The graphs in Fig. 4 show that the ViT-B_16 model's accuracy goes up steadily during training, but there are big ups and downs in the validation set. This increase in validation loss and instability suggests that the model sometimes learns too much from the training data, which may limit how well it performs on new data. In particular, the increase in validation loss and instability indicates that the model overfits the dataset occasionally, and its generalization capacity may be limited.

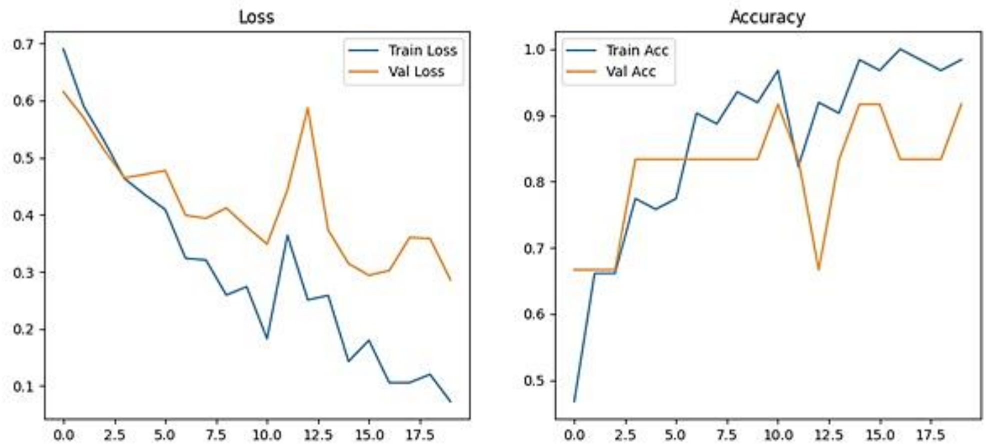


Figure 4. Accuracy and loss graph for the ViT-B_16 model

According to the confusion matrix presented in Fig. 5, the ViT-B_16 model correctly classified 80% (8/10) of individuals with scoliosis and 83% (5/6) of normal individuals. The misclassifications resulted in an error rate of 20%, especially for individuals with scoliosis. The area under the ROC curve (AUC) value shown in Fig. 6 is 0.90, indicating that the model is generally capable of discriminating between classes. These metrics show that the model has a balanced performance and shows promise for clinical decision support systems.

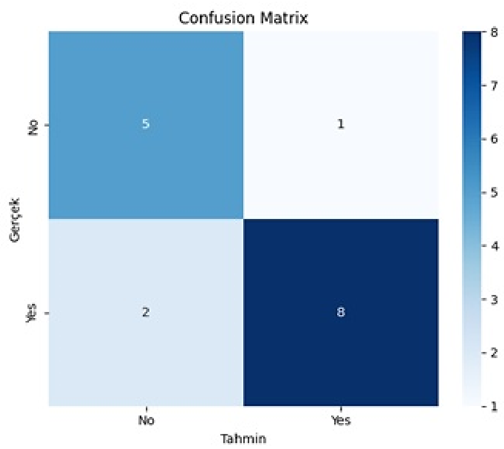


Figure 5. *Confusion matrix of the ViT-B_16 model*

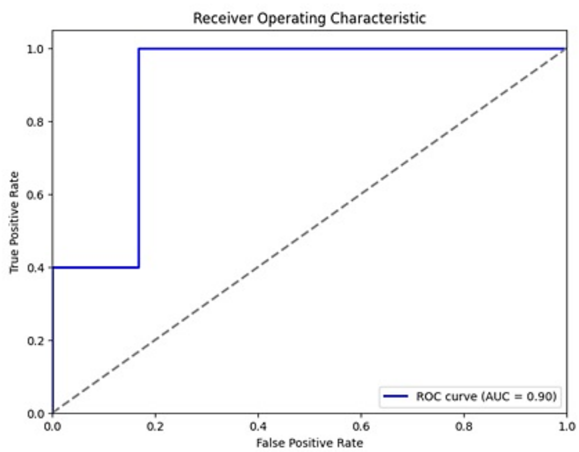


Figure 6. *ViT-B_16 ROC Curve*

The metrics presented in Table 4 show that the ViT-B_16 model has an overall accuracy of 81% and can classify individuals with scoliosis with an F1-score of 84%. The model exhibits high selectivity in the positive class (0.89%), while the precision in the negative class is relatively low (0.71%), indicating a partial performance difference between the classes. However, the close and balanced distribution of macro and weighted averages suggests that the model provides a consistent classification performance overall.

Table 4. *Classification Performance Metrics for ViT-B_16 Model*

Class	Precision	Recall	F1-Score	Support
No	0.71	0.83	0.77	6
Yes	0.89	0.8	0.84	10
Accuracy			0.81	16
Macro Avg	0.8	0.82	0.81	16
Weighted Avg	0.82	0.81	0.81	16

3.3. Efficient-B0 Model Metric Outputs

In the graphs presented in Fig. 7, it is seen that the loss value of the Efficient-B0 model decreases steadily during the training process, while the accuracy value increases gradually. However, the accuracy and loss values of the validation set follow a stagnant trend from the early epochs, indicating that the generalization capacity of the model is limited. The early stabilization and low level of the validation accuracy indicate that the model tends to overfit. This analysis reveals that the Efficient-B0 model provides a high fit to the training data but fails to maintain similar success on the validation data.

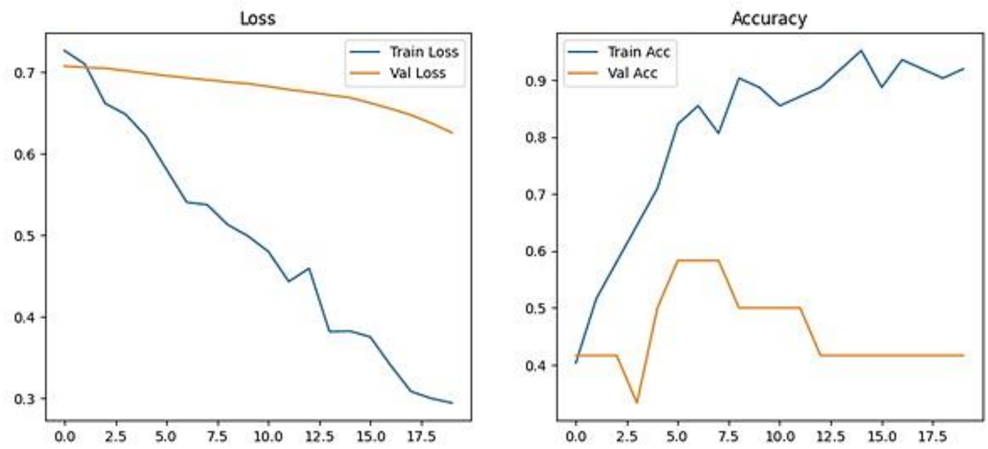
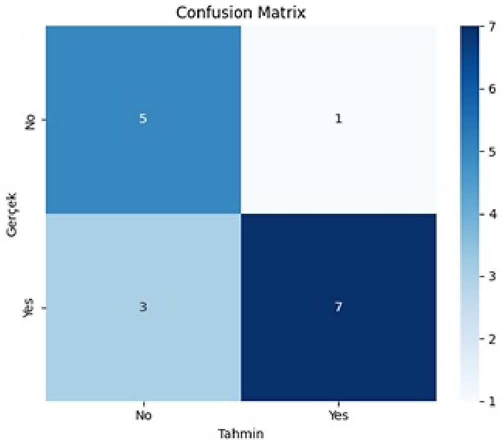


Figure 7. *Accuracy and loss graph for the Efficient-B0 model*

The confusion matrix in Fig. 8 shows that the Efficient-B0 model accurately identified 70% of people with scoliosis and 83% of normal individuals. However, there were three cases where it missed detecting scoliosis, indicating that the model struggles to recognize individuals with this condition. We observed three false negatives in the positive class, suggesting that the model's sensitivity in recognizing individuals with scoliosis is limited. The area under the ROC curve (AUC) in Fig. 9 is 0.78, indicating that the discrimination level of the model between classes is moderate. These findings show that the Efficient-B0 model can perform the basic classification task but is weaker than the other models in terms of overall accuracy and generalization performance.



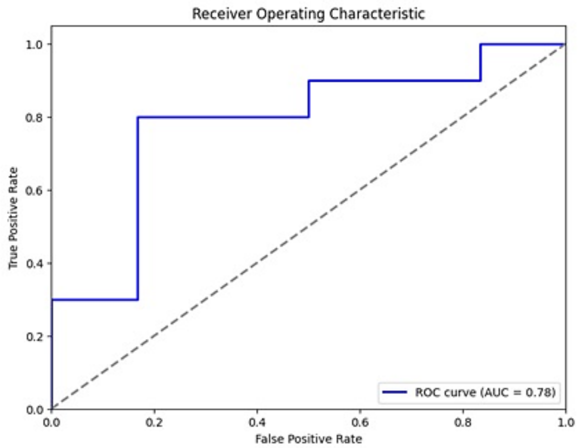


Figure 8. *Confusion matrix of the Efficient-B0*

Figure 9. *Efficient-B0 ROC Curve*

The metrics presented in Table 5 show that the overall accuracy of the Efficient-B0 model is 81% with an F1-score of 0.84 for the positive class (individuals with scoliosis). The model is excellent at finding scoliosis cases (0.89%), but it struggles with correctly identifying people without scoliosis (0.71%), indicating it has trouble with uneven class sizes. Macro and weighted averages are close to each other, suggesting that the model offers balanced but limited generalization performance overall.

Table 5. *Classification Performance Metrics for Efficient-B0 Model*

Class	Precision	Recall	F1-Score	Support
No	0.71	0.83	0.77	6
Yes	0.89	0.8	0.84	10
Accuracy			0.81	16
Macro Avg	0.8	0.82	0.81	16
Weighted Avg	0.82	0.81	0.81	16

3.4. ResNet-50 Model Metric Outputs

The graphs in Fig. 10 show a steady decrease in the loss value and a significant increase in accuracy during the training process of the ResNet-50 model. However, the increase in the validation loss after the 10th epoch and the fact that the validation accuracy remains constant indicate that the model tends to overfit. The fact that the training accuracy reaches almost 100% while the validation accuracy remains constant and relatively lower indicates that the model overfits the training data. The result suggests that the generalization performance of the model may be limited.

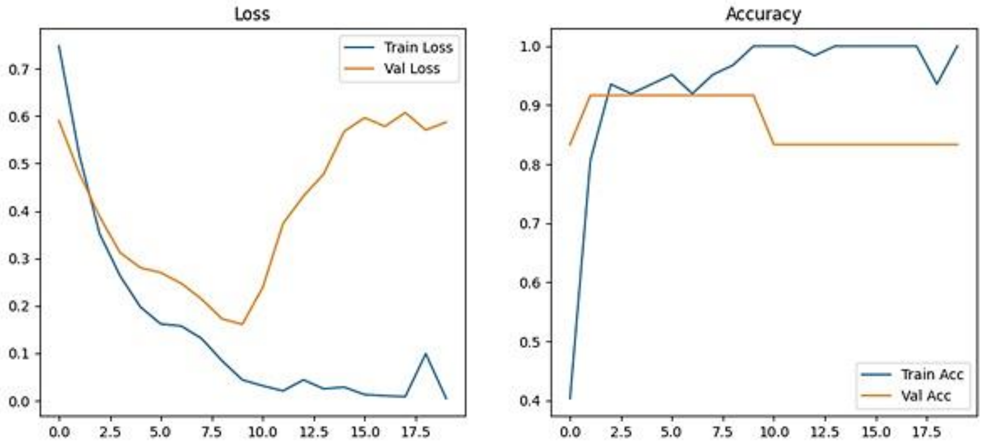
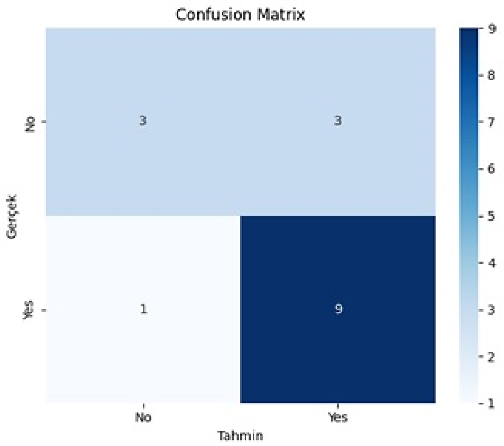


Figure 10. *Accuracy and loss graph for the ResNet-50 model*

According to the confusion matrix presented in Fig. 11, the ResNet-50 model correctly classified 90% (9/10) of the individuals with scoliosis, while it accurately predicted only 50% (3/6) of the individuals without scoliosis. This result shows that the model is more sensitive to the positive class but has a low discriminative capacity for the negative class. According to the ROC curve in Fig. 12, the AUC value of the model was calculated as 0.83, indicating that the discrimination ability between classes is at a medium-high level. In conclusion, while the ResNet-50 model performed strongly in the detection of individuals with scoliosis, the number of false positive classifications remained relatively high.



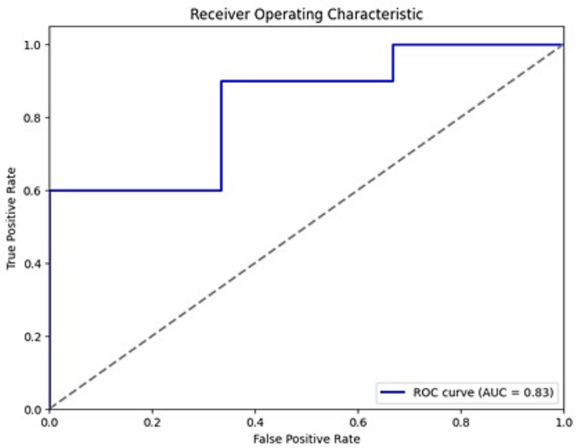


Figure 11. *Confusion matrix of ResNet-50*

Figure 12. *ResNet-50 ROC Curve*

According to the results presented in Table 6, the overall accuracy of the ResNet-50 model is 75%, and the F1-score in the positive class (individuals with scoliosis) is as high as 0.82. In the negative class, however, the recall rate is only 0.50, indicating that the model has limited success in discriminating individuals without scoliosis. The relatively low macro and weighted means suggest that class imbalance has a negative impact on model performance.

Table 6. *Classification Performance Metrics for ResNet-50 Model*

Class	Precision	Recall	F1-Score	Support
No	0.75	0.5	0.6	6
Yes	0.75	0.9	0.82	10
Accuracy			0.75	16

Macro Avg	0.75	0.7	0.71	16
Weighted Avg	0.75	0.75	0.74	16

3.5. ConvNeXt Model Metric Outputs

According to the graphs presented in Fig. 13, the ConvNeXt model shows both a decrease in loss values and an increase in accuracy rates during training. The fact that the training and validation losses are close to each other suggests that the risk of overlearning is low. Overall, the model demonstrated a strong learning capacity, achieving high accuracy levels in both training and validation phases.

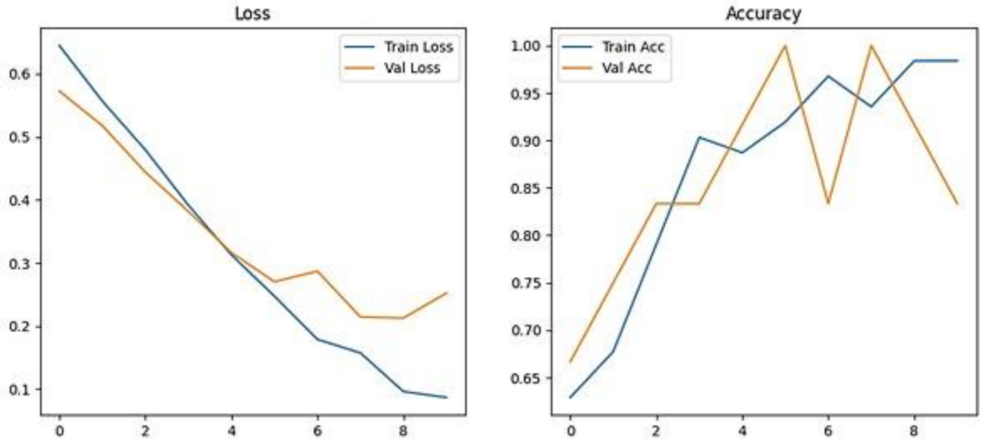
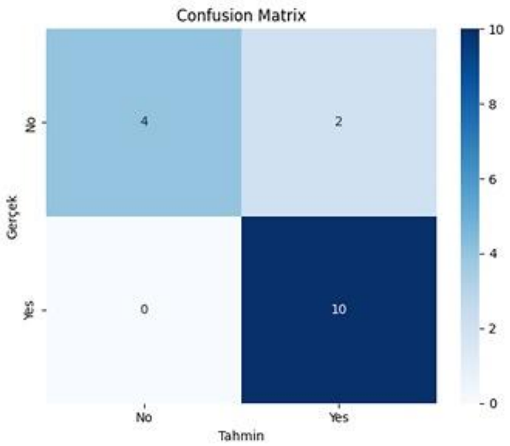


Figure 13. *Accuracy and loss graph for the ConvNeXt model*

According to the confusion matrix presented in Fig. 14, the ConvNeXt model classifies individuals with scoliosis with 100% accuracy (10/10), while achieving a 67% accuracy rate (4 out of 6) for identifying individuals without scoliosis. This result indicates that the model exhibits a very high sensitivity in the positive class. The AUC value of the ROC curve shown in Fig. 15 is 0.95, indicating that the overall classification performance of the model is high.



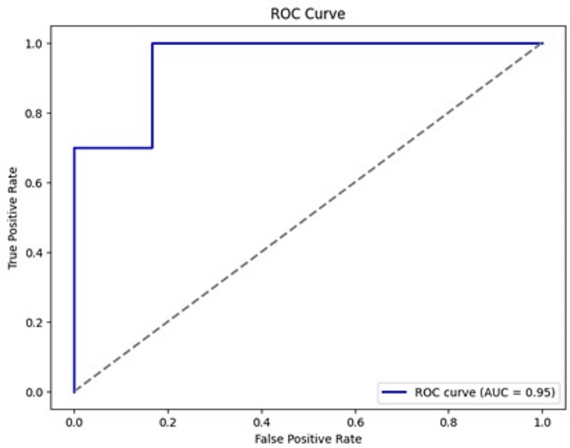


Figure 14. *Confusion matrix of the ConvNeXt*

Figure 15. *ConvNeXt ROC Curve*

The metrics presented in Table 7 show that the ConvNeXt model has an overall accuracy of 88% and classifies individuals with scoliosis with high success, with 100% recall and a 0.91% F1-score. Although the model exhibited high precision (1.00%) in the negative class, the recall value of 0.67% suggests that it offers limited sensitivity for individuals without scoliosis.

The model consistently performs without significant inter-class imbalance, as indicated by the high macro and weighted mean scores. These findings suggest that the ConvNeXt model is a strong candidate for clinical applications, especially for accurate detection of the positive class.

Table 7. *Classification Performance Metrics for the ConvNeXt Model*

Class	Precision	Recall	F1-Score	Support
No	1	0.67	0.8	6
Yes	0.83	1	0.91	10
Accuracy			0.88	16
Macro Avg	0.92	0.83	0.85	16
Weighted Avg	0.9	0.88	0.87	16

3.6. Model Performance Evaluation

We evaluated the metric outputs of DenseNet121, our most successful model, and briefly explained the model outputs.

3.6.1. ROC Curve and AUC Value

The ROC (Receiver Operating Characteristic) curve of the model is a general indicator of classification performance. The area under the ROC curve (AUC) value obtained in this study was calculated as 0.98. This high AUC value indicates that the model discriminates positive (scoliosis) and negative (normal) samples with very high accuracy. The slope of the ROC curve reveals that the false positive rate is low, and the true positive rate is high, indicating that the model is clinically reliable in scoliosis screening.

3.6.2. Confusion Matrix Results

The classification performance of the model is summarized by the confusion matrix based on four key metrics. Accordingly, the model correctly classified 5 cases as negative (TN) and incorrectly predicted only 1 case as positive (FP). Similarly, 1 positive sample was incorrectly identified as negative (FN), whereas 9 positive samples were correctly identified (TP). This distribution shows the overall accuracy of the model as well as its success in recognizing positive classes. According to this matrix, five of the six people who don't have scoliosis receive the correct classification, while one receives the incorrect one. Of the 10 individuals with scoliosis, 9 were correctly classified and 1 was misclassified. This indicates that the model has a balanced performance in terms of both recall and precision. In line with these results, the model:

- It detected negative (non-scoliosis) cases with 83% accuracy (5/6),
- In positive cases (with scoliosis), it achieved 90% accuracy (9/10),
- The overall accuracy was 88%.

On the other hand, the precision, recall, and F1-score values for the “Yes” class are 0.90. This value indicates that the model correctly classifies individuals with scoliosis with 90% accuracy and successfully detects 90% of true positive examples. The high scores in the “Yes” class reflect the model's strong performance in recognizing individuals with scoliosis. The overall accuracy rate was 88%. This statistic means that 14 out of the total 16 samples tested were correctly classified.

Macro Avg (0.87) shows the average performance across classes with equal weight, while Weighted Avg (0.88) presents the overall average, taking into account the distribution of classes in the dataset. Here, a high weighted average value indicates that class imbalance does not negatively affect model performance. The Support column shows the number of instances of each class in the test set: 6 instances for the "No" class and 10 instances for the "Yes" class. The sample test images presented in Fig. 16 show that the proposed method can detect individuals with scoliosis with high accuracy. In the vast majority of the images, the model's prediction is in agreement with the true label, with only a few instances of classification error. This study indicates that the model based on back surface images can both successfully detect visual deformations and be a clinically applicable decision support tool.

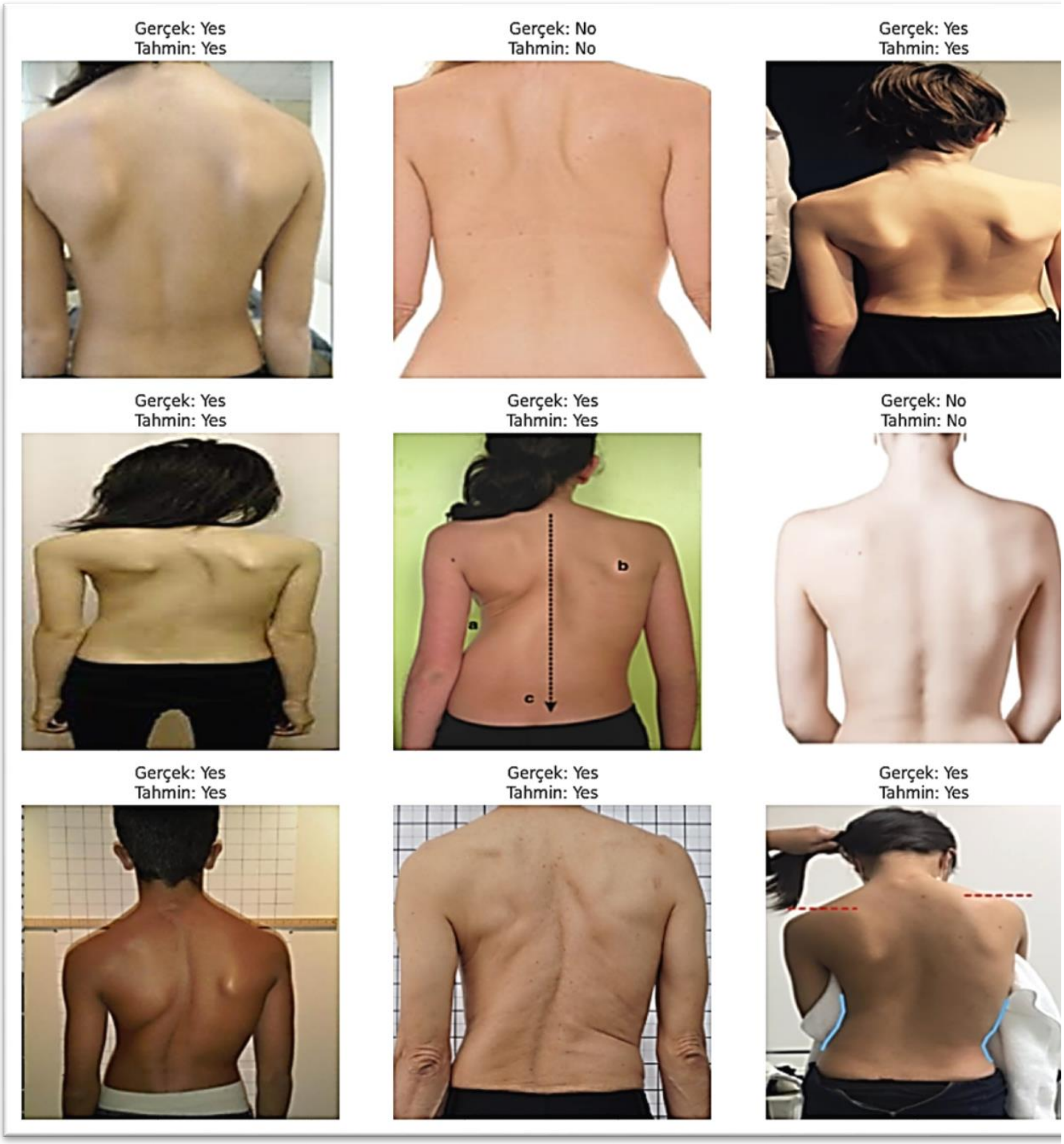


Figure 16. *Displays the prediction images generated by the proposed mode*

3.7. Discussion and Limitations

Accuracy values in the literature range from 70.2% to 94%. The result of our study is 88% accuracy. It can be considered a strong result, especially when compared to 94% (3D sensor) and 93% (smartphone photos). However, differences in the datasets (e.g., 3D sensor vs. 2D images) may limit direct comparison of our study. The lack of a study using the same dataset in the literature leads to an indirect comparison. Also, some studies reported accuracy for Cobb angle measurement, but due to the binary classification (scoliosis present/absent) context of your study, these measurements are not directly comparable. In addition, the "black box" nature of machine learning-based models imposes certain limitations in terms of both accuracy and reliability in clinical decision support domains such as scoliosis. This lack of inherent transparency may reduce the interpretability of the decision-making mechanisms of the models, negatively affecting the confidence of both clinicians and patients in the model output. Therefore, in addition to the integration of methods to improve model explainability, validation of the developed systems with clinical experts is also a critical requirement.

4. CONCLUSION

The results of the study show that DL models are effective tools for scoliosis detection using back surface images. Although scoliosis diagnosis traditionally relies on X-ray imaging, this study proposes a radiation-free, non-invasive DL approach for automatic scoliosis detection and classification using back surface images, demonstrating feasibility for portable and rapid screening systems. However, the study's limited image set necessitates testing on larger, multicenter datasets. We also suggest adding more clinical data to categorize based on the severity of scoliosis. In visual prediction analyses, the models correctly classified bare back deformations and identified individuals with suspected scoliosis with a high degree of accuracy. The findings could contribute to further treatment planning and monitoring for the patient by providing computer-aided real-time assessments to assist physicians in management decision-making.

In the future, these models have the potential to be used in mass screening or as clinical pre-assessment tools. The study demonstrates the potential of the proposed method in clinical screening. The high accuracy, AUC, and classification scores obtained in the study provide a low-cost, rapid, and safe alternative for early diagnosis of scoliosis. The absence of radiation risk is an important advantage for large-scale screening programs, especially in children and adolescents. In conclusion, we find that DL models using back surface images are effective for scoliosis detection and can enhance existing diagnostic methods, indicating that these models may be clinically reliable for scoliosis screening. Future studies should aim to increase the generalizability of the method by expanding the dataset and validating it in different age groups. In the case of mobile application integration, it is thought to be an easily accessible service provider.

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2.1. Kamusal Alanda Siber Güvenlik

Kuruluşlar, dış veya iç kaynaklardan kaynaklanan siber saldırılara maruz kaldığında bu değerli kaynağı korumak giderek zorlaşmakta, böylece kuruluşun ve bilgilerinin güvenliği tehlikeye girmektedir (Tu ve diğerleri, 2018).Bu durum bütün kuruluşlar için önemli bir durum olsada kamu kurumları ellerinde bulunan veriler nedeniyle daha kritik bir öneme sahiptir. Bunun nedeni, kamusal alanın özel sektöre kıyasla daha geniş ve yaygın bir kullanıcı tabanını kapsamasıdır (Aman ve Al Shukaili, 2021). Araştırmalar, güvenlik ihlallerinin yaklaşık yüzde yetmişinin kamu veya devlet kuruluşlarına yönelik olduğunu göstermektedir (Aman ve Al Shukaili, 2021).Bu siber saldırılara karşı alınabilecek önlemlerin bireysel farkındalık eğitiminin önemli bir parçası olduğu düşünülmektedir. Türkiye'de kamu kurum ve kuruluşlarında çalışanların bilgi güvenliği farkındalıklarının düşük olduğu çeşitli araştırmalarla ortaya konmuştur (Çakır ve Taşer, 2023; Kahriman, 2022) Ayrıca, Catota ve arkadaşları (2019) farkındalık ve eğitimle öğrenenlerin "belirli saldırı türlerine karşı savunma önlemleri almada aktif rol kazanabileceğini" vurgulamıştır (s. 16).Bu çalışma ile bu farkındalığın bağlı olduğu faktörler ve geliştirilmesi için planlamanın dikkat edileceği hususların belirlenmesine kaynak sağlanması öngörülmektedir.

2.2. Siber Güvenlik Farkındalık Eğitimi

Sayısız çalışma, siber güvenlik farkındalığını (SGF) artırmanın en etkili yöntemlerinden birinin kuruluşlarda eğitim programları uygulamak olduğunu öne sürmüştür (Alkhazi ve diğerleri, 2022).Özellikle ulusal anlamda kritik bilgileri ellerinde bulunduran ve erişim yetkisi bulunan kamu kuruluşlarında siber güvenlik farkındalığı eğitimlerinin önemi büyüktür. Çünkü eğitim yoluyla SGF'yi yaymak, insanları tehditleri hafifletme ve zararı en aza indirme konusunda daha yetenekli hale getirebilir (Shillair ve diğerleri, 2022). Aslan (2022) ise sistematik tatbikatlar ve düzenli eğitimlerin siber güvenlik farkındalığını artırdığını, ancak bu etkinin sürdürülebilir olması için kurumsal politikaların gerekliliğini vurgulamıştırLiteratürde, kuruluşların farkındalık eğitim programlarını nasıl geliştirmesi gerektiğine dair çok sayıda rehber sunulmaktadır. Bu çalışma ile farkındalık eğitimlerinde planlama hususunda hangi özelliklere dikkat edileceğine ışık tutacaktır.

2.3. Sosyal Mühendislik Tehditleri

Sosyal mühendislik, insan zayıflıklarını istismar etme doğası nedeniyle günümüzün daha zorlu siber güvenlik tehditlerinden biri olarak ortaya çıkmıştır (Aldawood ve Skinner, 2018).Sosyal mühendislik saldırıları teknik saldırılardan ziyade insanı psikolojik olarak manupile edilerek gerçekleşen saldırılardır. Sosyal mühendislik yöntemlerini kullanan saldırganlar, yalnızca evlerindeki bireyleri değil, aynı zamanda bu ortamlarda çalışan insanları hedefleyerek tüm kurumları ve şirketleri manipüle etmeye çalışırlar (Al-Otaibi ve Alsuwat, 2020). Bu saldırılar; phishing (oltalama), spear phishing (hedefli oltalama), vishing (telefon yoluyla oltalama), pretexting (bahane uydurma), baiting (yemleme) ve quid pro quo (çıkar karşılığı) gibi farklı tekniklerle uygulanmaktadır (Hadnagy, 2018). Kamu kurumlarında yapılan farkındalık çalışmalarının sosyal mühendislik saldırılarına karşı koruma sağlama açısından teknik güvenlik önlemlerinden daha kritik olduğu vurgulanmaktadır (Jansson & von Solms, 2013). Bununla birlikte, farkındalık düzeyinin eğitim, yaş, dijital okuryazarlık ve daha önce saldırıya maruz kalma deneyimi gibi değişkenlerle farklılaştığı görülmektedir (Alotaibi, Furnell & Clarke, 2016).Bu çalışma ile sosyal mühendislik saldırılarında kamu sektörü, çalışma yılı, eğitim seviyesi, yaş ve cinsiyet faktörlerinin farkındalığa ve sosyal mühendislik tehditlerine etkisi göz önüne serilecektir.

3. Yöntem

Bu araştırma, nicel araştırma yöntemi kullanılmıştır.Veri setini, Türkiye'nin farklı illerinde görev yapan toplam 303 kamu çalışanı oluşturmaktadır. Katılımcılar, yaş, cinsiyet, eğitim düzeyi, görev yaptıkları kamu sektörü ve çalışma süresi değişkenleri açısından çeşitlilik göstermektedir.

Veri toplama aracı olarak iki bölümden oluşan bir anket formu kullanılmıştır. İlk bölüm, katılımcıların demografik bilgilerini (yaş, cinsiyet, eğitim durumu, görev yaptığı kamu sektörü ve çalışma süresi) toplamaya yönelik sorulardan oluşmuştur. İkinci bölüm ise katılımcıların bireysel siber güvenlik farkındalık düzeylerini ölçmeye yönelik beşli Likert tipinde hazırlanmış soruları içermektedir. Ölçek maddeleri, kablosuz ağ güvenliği, bilgisayar güvenliği, mobil cihaz güvenliği, kimlik doğrulama alışkanlıkları, parola yönetimi, kamuya açık ağlarda davranış, bankacılık güvenliği, sosyal medya, kişisel bilgi güvenliği ile kimlik avı farkındalığı gibi başlıklarda toplanmaktadır. Yanıt seçenekleri "Hiçbir zaman" (1 puan), "Nadiren" (2 puan), "Bazen" (3 puan), "Sıklıkla" (4 puan) ve "Her zaman" (5 puan) şeklinde puanlanmıştır. Ancak riskli davranışları ölçen belirli maddeler için ters puanlama yapılmıştır. Bu kapsamda; "Root kırma ve mağaza dışı uygulama indirme", "Şifrelerin güvenli olmayan bir yerde saklanması" ve "Kamuya açık Wi-Fi'de şifreli işlem yapılması" maddelerinde güvenli davranış yüksek puan, riskli davranış ise düşük puan alacak şekilde değerlendirilmiştir.

Her katılımcının toplam farkındalık puanı, tüm maddelerden elde edilen puanların toplanmasıyla hesaplanmış ve bu değer mümkün olan maksimum puana bölünerek yüzde cinsinden farkındalık düzeyi elde edilmiştir. Araştırma verileri Google Forms aracılığıyla çevrim içi olarak toplanmış, gönüllülük esasına göre uygulanmıştır. Katılımcılara araştırmanın amacı, gizlilik ilkeleri ve verilerin yalnızca bilimsel amaçla kullanılacağı bilgisi verilmiştir. Veri toplama süreci yaklaşık dört hafta sürmüştür.

Elde edilen veriler IBM SPSS Statistics ve Microsoft Excel programları ile analiz edilmiştir. Analizlerde tanımlayıcı istatistikler, korelasyon analizi, gruplar arası karşılaştırmalar (ANOVA, Kruskal-Wallis Testi, Chi-Square Testi, Mann-Whitney U Testi) ve faktör analizi kullanılacaktır. Ayrıca her bir demografik grup için ortalama farkındalık yüzdesi hesaplanmış, en yüksek farkındalık düzeyine sahip gruplar tespit edilmiştir.

4. Bulgular

Araştırmaya toplam 303 kamu çalışanı katılmıştır. Genel siber güvenlik farkındalık düzeyi, ters puanlama uygulanmış maddeler de dikkate alınarak hesaplandığında **%72,0** olarak bulunmuştur. Katılımcıların **197'si erkek** olup bu grubun ortalama farkındalık düzeyi **%73,7**, **106'sı kadın** olup ortalama farkındalık düzeyi **%68,8**'dir. Eğitim düzeyi açısından en yüksek ortalama doktora mezunlarında (%75,0) ve yüksek lisans mezunlarında (%73,6) gözlenmiştir. Ortaöğretim/ilköğretim grubunda ise farkındalık düzeyi en düşük seviyede (%66,8) tespit edilmiştir.Sektörel dağılım incelendiğinde, farkındalık düzeyi en yüksek grubun güvenlik sektöründe (%75,1) yer aldığı, bunu sağlık sektörünün (%71,4) ve eğitim sektörü (%70,0) takip ettiği görülmektedir. Diğer sektöründe çalışanların ortalama farkındalık düzeyi ise %68,0 ile en düşük seviyededir.Yaş gruplarına göre değerlendirildiğinde, en yüksek farkındalık düzeyi 30-39 yaş katılımcılarda (%74,5) gözlenmiştir. Bunu %73,1 ile 60 yaş ve üzeri yaş grubu izlemektedir.

En düşük farkındalık düzeyi ise %69,9 ile 40-49 yaş grubunda yer almaktadır.Çalışma süresi değişkeni incelendiğinde, 10 yıl ve üzeri deneyime sahip katılımcıların farkındalık düzeyi %75,0 ile en yüksek seviyededir. 6-10 yıl arası çalışanlarda bu oran %72,0 iken, 0-1 yıl arası çalışanlarda %68,6 ile en düşük seviyeye gerilemektedir.

Tablo 1. *Demografik Değişkenlere Göre Ortalama Farkındalık Düzeyleri*

Demografik Değişken	Grup	Katılımcı Sayısı	Ortalama Farkındalık (%)
Cinsiyet	Erkek	197	73,7
	Kadın	106	68,8
Eğitim	Ortaöğretim / İlköğretim	2	66,8
	Lise	34	72,2
	Ön lisans	40	70,4
	Lisans	180	71,8
	Yüksek lisans	37	73,6
	Doktora	10	75,0
Sektör	Güvenlik (TSK, Emniyet, Jandarma)	102	75,1
	Eğitim	85	70,0
	Sağlık	92	71,4
	Diğer	24	68,0
Yaş	18-29	143	70,8
	30-39	101	74,5
	40-49	40	69,9
	50-59	14	71,5
	60 ve üzeri	5	73,1
Çalışma Süresi	0-1 yıl	58	68,6
	2-5 yıl	107	71,6
	6-10 yıl	60	72,0
	10 yıl ve üzeri	78	75,0

5. Sonuç ve Öneriler

Bu çalışmanın, kamu sektöründe süreklilik sağlayan bir siber güvenlik farkındalık kültürünün gelişmesine katkı sağlaması ve geliştirilecek politikalara ve eğitim stratejilerinde bilimsel bir veri çalışması sunması hedeflenmektedir. Bu çalışmada anket verileri, 5'li Likert ölçeğine dayalı olarak puanlanmış ve belirli sorular ters puanlama yöntemi ile değerlendirilmiştir. Elde edilen sonuçlara göre, genel siber güvenlik farkındalık düzeyi %72,0 olarak bulunmuştur. Bu orana göre kamu çalışanlarının genel bireysel farkındalık seviyesinin orta-üst seviyede olduğunu ancak gelişimi ihtiyacı olduğunu göstermektedir.

Demografik analizlere göre, erkeklerin ortalama farkındalık düzeyinin kadınlara göre biraz daha yüksek olduğunu, eğitim düzeyinde doktora mezunlarının en yüksek ortalamaya sahip olduğunu ortaya koymuştur. .Görev yaptığı kamu sektörü dağılımda güvenlik sektöründe çalışanlar en yüksek farkındalık seviyesinde gözükürken, diğer sektöründe farkındalık düzeyi daha düşük bulunmuştur. Yaş gruplarına bakıldığında, 30-39 yaş grubu katılımcılar en yüksek farkındalık düzeyine sahipken, 40-49 yaş grubunda bu oran en düşük seviyededir. Çalışma süresi açısından ise 10 yıl ve üzeri deneyime sahip katılımcılar, en yüksek farkındalık seviyesine sahip olduğu gözlemlenmiştir.

Bu çalışma kapsamında elde edilen veriler, yalnızca mevcut durumun genel bir ortalamasını göstrmektedir. İlerleyen aşamalarda IBM SPSS Statistics programında gerçekleştirilecek korelasyon analizi, gruplar arası karşılaştırmalar (ANOVA, Kruskal-Wallis Testi, Chi-Square Testi, Mann-Whitney U Testi) ve faktör analizleri ile değişkenler arasındaki istatiksel ilişkilerin anlamlılığı ortaya konacaktır. Ayrıca, yapılacak istatistiksel testler ile farkındalık düzeyinin hangi faktörlerden en çok etkilendiği belirlenebilecektir.

Bu çalışma kamu çalışmalarının bireysel siber güvenlik farkındalık düzeyleri konusunda başlangıç olarak bir inceleme ve fikir sunmaktadır. Bu verilerin istatistiksel olarak daha derin bir şekilde incelenmesiyle, gelecekte bireysel siber güvenlik farkındalığının arttırılması için uygulanacak eğitim ve politika geliştirme süreçleri daha etkili ve verimli bir şekilde tasarlanabilecektir.

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