International Information and Engineering Technology Association
Advancing the World of Information and Engineering

Ingénierie des Systèmes d'Information
Vol. 31, No. 3, March, 2026, pp. 977-983
Journal homepage: http://iieta.org/journals/isi

Symmetry Index-Guided Automatic Labeling with AlexNet for Lumbar Spine Muscle Classification

Inaam Salman Aboud

College of Education, Mustansiriya University, Baghdad 10001, Iraq

Corresponding Author Email: inaamsalman89@uomustansiriyah.edu.iq

https://doi.org/10.18280/isi.310327

Received: 12 November 2025
Revised: 25 January 2026
Accepted: 17 March 2026
Available online: 31 March 2026

Keywords:
lumbar spine muscle classification, Symmetry Index, automatic labeling, AlexNet, transfer learning, medical image analysis

ABSTRACT

Manual annotation is time-consuming and subjective, but accurate classification of lumbar spine muscle symmetry is crucial in the evaluation of musculoskeletal disorders. The paper will present a deep learning model that combines automatic labelling with transfer learning to classify lumbar muscles as symmetric or asymmetric. The ground truth labels are created automatically by the introduction of a Symmetry Index (SI) to measure pixel-level intensity differences between left and right muscle regions. It is important to note that the SI is not used as a feature when training a model but is only annotated. The pipeline suggested consists of image preprocessing, intensity normalization, and dataset partitioning (70% training, 15% validation, 15% testing). Pre-trained AlexNet is fine-tuned to the binary classification task. To fairly compare, two classical machine learning models, support vector machine (SVM) and k-nearest neighbors (KNN) using Histogram of Oriented Gradients (HOG) features are used as baselines. According to the results of the experiment, the proposed AlexNet model demonstrates the accuracy of 86.27% which is much higher than the accuracy of KNN (74.51%) and SVM (50.98%). The higher scores of F1 demonstrate the superiority of deep learning (85.71%) as compared to traditional methods (KNN: 71.11%, SVM: 0%). Confusion matrix analysis shows that AlexNet is balanced in its classification of the symmetric and asymmetric cases but SVM does not recognize the minority at all. These results indicate that symmetry-based automatic labelling and transfer learning have provided an effective, scalable and annotation efficient solution to the lumbar spine muscle classification of medical images.

1. INTRODUCTION

The lumbar spine muscles are crucial to the diagnosis and evaluation of musculoskeletal diseases whereby correct analysis of the muscle symmetry is paramount in determining the disease pathology. Nonetheless, manual evaluation is still time consuming and may be prone to inter-observer variability, thus possibly influencing diagnostic consistency and reliability. To address these shortcomings, this study suggests a hybrid system, which combines an automated labeling system and a deep learning-based classification system. The suggested method is developed to minimize the need to rely on manual annotation but achieve good classification rates. Within this paradigm, a labeling strategy is initially adopted which is automatic and generates ground-truth annotations and then the ground-truth annotations are used to train a convolutional neural network (CNN) to perform classification tasks.

The primary contribution of this work is that symmetry-based automatic labelling mechanism is integrated with a deep learning system, reducing the human influence to the minimum, and maintaining the accuracy of the classification. Moreover, the originality of the suggested work is shown regarding the creation of a scalable annotation approach that uses the symmetry information for label generation and a transfer learning-based classification model that improves automation and minimizes the need of manual labels in medical image analysis applications. Maintaining structural stability of the body, and its overall functionality, is basically reliant on the lumbar spine [1]. Any dysfunction or asymmetry in Multifidus and Erector spinae muscles that occur are the cause of Low back pain.

So, this region Muscles are considered the basic elements for spinal support, load management, and trunk mobility [2].

Lumbar multifidus has received great interest from investigators and practitioners focusing on the management of lumbar pain and motor recovery. It is worth noting that it presents possible and objective wherewithal for evaluating muscle morphology and functional capacity [3].

There are many problems caused by the long duration and the inter-observer variability in the manual analysis of imaging data used in the Traditional assessments of lumbar muscle conditions. So, for improving the accuracy and efficiency, advance computational methods were used, leading to a shift toward automating lumbar muscle analysis. Machine learning has become a systematic shift in medical imaging. It rephrases the diagnostic workflow and supports more informed clinical decision-making.

Actually, the study validates the Machine learning application in various imaging modalities, such as X-ray, CT, MRI and ultrasound with a particular focus on image acquisition, processing and analysis. Convolutional neural networks (CNNs) and support vector machines (SVMs) can be used to classify diseases, predictive models and tumor detection tasks, which can be useful in the early diagnosis of the disease and assist in personalized treatment plans. Despite this, there are still several challenges, including enhancing the interpretability of models, ethical issues of patient privacy and quality of data [4]. The performance of CNN-based deep learning methods has been very high, with learning hierarchical features directly represented of raw imaging data. The study led to the fact that CNNs are capable of high accuracy of lumbar muscle segmentation and classification, which is many times better than the traditional ML methods [1].

1.1 AlexNet

AlexNet is a CNN that has demonstrated good performance on image classification and has earned considerable recognition through ImageNet Large Scale Visual Recognition Challenge (ILSVRC), it allows the classification of 1,000 categories of objects and is considered one of the first large-scale applications of deep CNNs. Introduced in 2012 by Alex Krizhevsky, along with Ilya Sutskever and Geoffrey Hinton at the University of Toronto, the network contains approximately 60 million parameters and 650,000 neurons, its substantial depth contributed to its exceptional performance, and the computational burden was mitigated by training on GPUs [5].

The network uses dropout as a regularization method for overfitting mitigating, while the ReLU activation function is applied for avoiding gradient vanishing [6].

1.1.1 AlexNet architecture

As shown in Figure 1, the architecture composes of eight layers. The initial five layers execute convolution operations, and the final three layers are composed of fully connected (FC), max pooling, and activation layers. ReLu activation function is used in this architecture. There are two dropout layers. SoftMax activation function is used by output layer. The size of image input is 227 × 227.

The configuration of training parameters in the AlexNet architecture significantly influences the optimization process, ensuring effective reduction of the loss function through weight adjustments across successive epochs. The aim is to increase the accuracy of the model by reducing the losses. Importance of parameters, such as learning rate, epochs and batch size, that used in training play an important role in the Parameter optimization [7].

1.1.2 Applications of AlexNet

The applications of AlexNet span multiple areas, such as medical imaging, image classification, transfer learning (TL), object detection, and fine-grained categorization, as described in the following sections [6]:

Image Classification: it is the first and most popular one. In 2012, it achieved significant performance in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) [8], achieving superior performance over earlier approaches, and these results confirmed the utility of deep CNNs for image recognition. The same architectures have been utilized for applications such as face recognition, medical imaging classification, and object identification; for example, Ghazal et al. [9] implemented CNNs in face recognition tasks. The study [9] proposed a transfer learning-based AlexNet model for autism detection using facial features of children. Features are extracted using the pre-trained AlexNet convolutional layers. The model uses these features to train a new FC layer. Evaluation on a Kaggle dataset comprising 2,940 autism-related images demonstrated that the proposed model outperformed existing approaches in terms of accuracy. Balashanmugam et al. [10] used an AlexNet model for iris image classification, obtaining a high recognition rate on 163,432 iris images, providing valuable insights for biometrics development. Kayadibi et al. [11] applied a pre-trained AlexNet for eye condition detection.

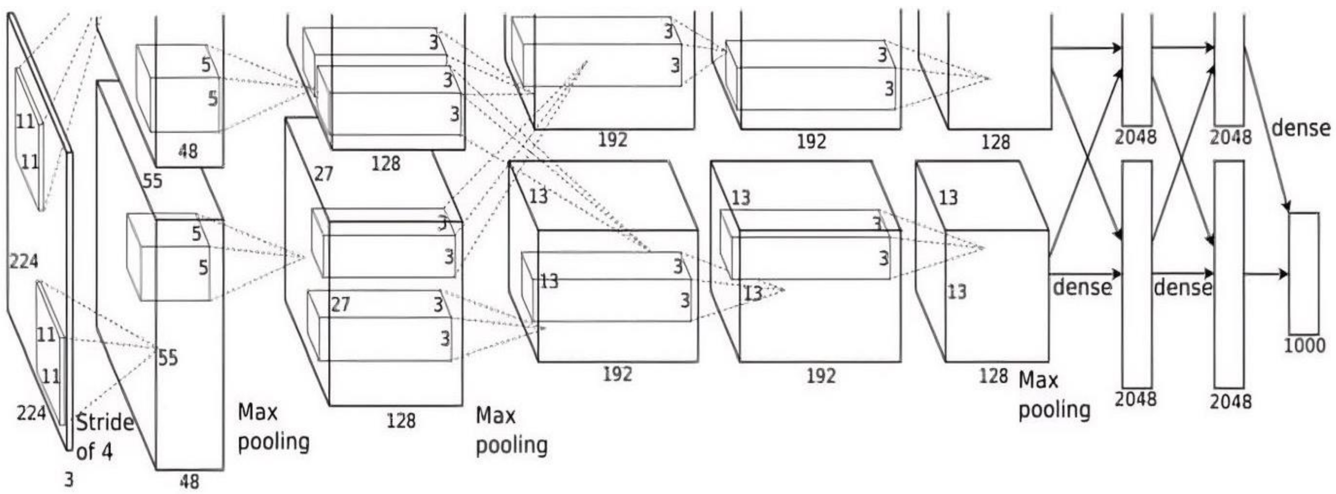

Figure 1. The architecture of AlexNet

Fine-Grained Classification: it includes recognizing between analogous categories within a wider class. AlexNet, capable of learning detailed and intricate features, is well-suited for tasks requiring fine-grained classification, including species-level recognition of birds [12], plant varieties [13, 14], or of canine maturity classification and bone fracture time [15]. The models were developed leveraging the foundational architecture of AlexNet to address these specific applications.

Medical Imaging: AlexNet's CNN model has shown relevance in medical imaging across multiple disease types. The model has been applied in medical images classification, like CT scans, MRIs, electroencephalograms, and X-rays, contributing to disease diagnosis, incorporating cancer [16], neurological disorders [17], and schizophrenia [18]. Healthcare professionals and researchers have improved the efficiency and accuracy for disease detection and diagnosis through applying AlexNet to medical data [8].

1.2 Related work

In this study by Yilihamu et al. [19], a retrospective dataset of 2500 patients were analyzed, including 2120 patients (25,554 images) for training, 80 patients (784 images) or internal validation, and 300 patients (3285 images) for external validation.

To simplify the analysis, both normal and mildly bulging discs were grouped as grades without significant pathological findings and the LDH region and the severity levels were defined according to the disc-spinal canal relationship. The automated training and validation stages used YOLOv8-based models: YOLOv8 for object localization and YOLOv8-seg for disc segmentation, and YOLOv8-pose for anatomical keypoint estimation. The reliability and consistency of the detection results were assessed in terms of the IoU, ME, precision, F1, Kappa and 95% CI.

The study by Liu et al. [20], introduces SpineSighter an AI-based framework that can be used to customize the management of NSLBP by classifying the patients into High Function (HF) and Low Function (LF) based on the dynamics of the spine. The system extracts the kinematic descriptors of angular displacement, velocity and acceleration using standard video recordings combined with computer vision algorithms in serial forward flexion trials. The model suggested provided strong classification results (accuracy: 95.13%, sensitivity: 93.81%, specificity: 96.00%, F1-score: 0.9442). The method focuses on velocity as a key biomarker of spinal activity and provides a basis of advanced and patient-specific therapeutic planning.

In this study, Hartley et al. [21] developed a machine learning model that they termed as BACK-to-MOVE for classifying NSLBP patients based on expert diagnostic labels, conventional video-related spinal kinematics, and PROMs. The data on motion was collected concurrently in 2D video and 3D format in forward flexion of 83 people. Two physiotherapists conducted the labeling into motor control impairment (MCI) and movement impairment (MI) and any discrepancies were decided upon by a third reviewer. For pose extraction, Higher HRNet CNN architecture was used, which is pretrained on the MS-COCO dataset and fine-tuned using feed-forward networks. Strong discriminative capability (accuracy = 93.98%, sensitivity = 96.49%, specificity = 88.46%, F1 = 0.957) was shown by the cross-validation (5-fold) and the pose estimation mean square error of 0.35° was used to verify its accuracy against 3D standards. But the incorporation of the PROMs characteristics resulted in low accuracy (68.67%) and specificity (18.52%).

In the study by Ruchi et al. [22], optimized feature extraction and selection methods were used in the detection of LSDs. The feature selection was done using a linearity based model so that only the most important features were selected to reduce the rate of misclassification. The first phase of the research was data acquisition, both real-time image recordings and benchmark magnetic resonance imaging (MRI) datasets. This was then followed by preprocessing phase to enhance quality of the data, this involved noise reduction using various methods such as median filtering, histogram equalization, normalization and data validation procedures. Background removal and region of interest (ROI) detection were then performed with the use of a region-cut strategy. For feature extraction, a differential spider monkey optimization (SMO) algorithm was used to find optimal representations, and feature selection was carried out with a CNN-based model with linearity restrictions.

Lastly, an ensemble-based classification model was used to predict diseases. Standard performance metrics, such as accuracy, specificity, sensitivity, and F-score were used to evaluate the proposed system. The results obtained showed high classification accuracy, with the multi support vector machine (MSVM) (96%) and random forest (RF) (94%) and decision tree (DT) (93.5%) and Naive Bayes (NB) (91%) all showing that the proposed approach was effective and reliable. The study by Mahesh et al. [23] adopts the proposed solution to run the X-ray images of both the public datasets and clinical scoliosis patients. A point-based automated system was presented that analyzed various spinal regions and provided credible diagnostic outcomes using a CNN. The performance of CNN was compared with that of a SVM classifier. The CNN model was accurate above 90% whereas SVM was above 60%. Future performance improvement and narrowing of this performance difference can be achieved by better image processing, more sophisticated feature extraction and an increase in high-quality annotated datasets.

In this work, Al-Kubaisi et al. [24] suggested a number of strategies to overcome the problem of a lack of training data in the classification of disc states and improve the overall effectiveness of the classification system. In particular, the transfer learning of other datasets was studied along with a novel region of interest (ROI) extraction method to enhance the relevance of features and the model learning ability. The experimental findings have shown that transfer learning from source domain that is highly related to the target dataset is much more effective in improving performance than the generic pre-trained models. Moreover, the combination of the ROI-based technique also increased the accuracy of the classification by 2% in VGG19, 16% in ResNet50, 5% in MobileNetV2 and 2% in VGG16. Further, the proposed approach showed further gains of 4% and 6% on VGG16 and VGG19 respectively, compared to the ImageNet transfer learning, which validated the usefulness of domain-relevant transfer learning, as well as ROI-based refinement of features.

The study by Mbarki et al. [25] on the creation of an automated system using deep CNNs to study magnetic resonance imaging (MRI) data at various contextual levels. The suggested method incorporates high-level feature representations to boost the network to identify intervertebral discs in the lumbar spine. These methods have proved to be effective and can be effectively applied to other image classification problems. More specifically, the authors used a CNN, which was based on the VGG16 architecture, for the recognition of herniated lumbar discs in MRI scans. The trained model demonstrated an accuracy of 94% which is a good level of performance and a state-of-the-art. In general, the suggested model is effective and efficient in detecting and diagnosing lumbar disc herniation. The main aim of the work is to help radiologists in diagnosis and treatment of lumbar herniated disc disease.

2. METHODOLOGY

The proposed approach is made through many stages. The research utilized an ultrasound imaging dataset offering reference data for the left and right lumbar multifidus muscles at five vertebral levels, collected under prone and standing conditions from 109 student-athletes participating in Concordia University's varsity sports teams [3]. Symmetry Index (SI) is employed to classify lumbar spine muscle images into two categories: Symmetry and Asymmetry. Unlike conventional approaches that rely on geometric features such as muscle area and eccentricity, the proposed method evaluates bilateral similarity using pixel-level intensity differences between the left and right regions of each image. It is important to note that the SI is used solely for generating class labels and is not used as an input feature for the deep learning model.

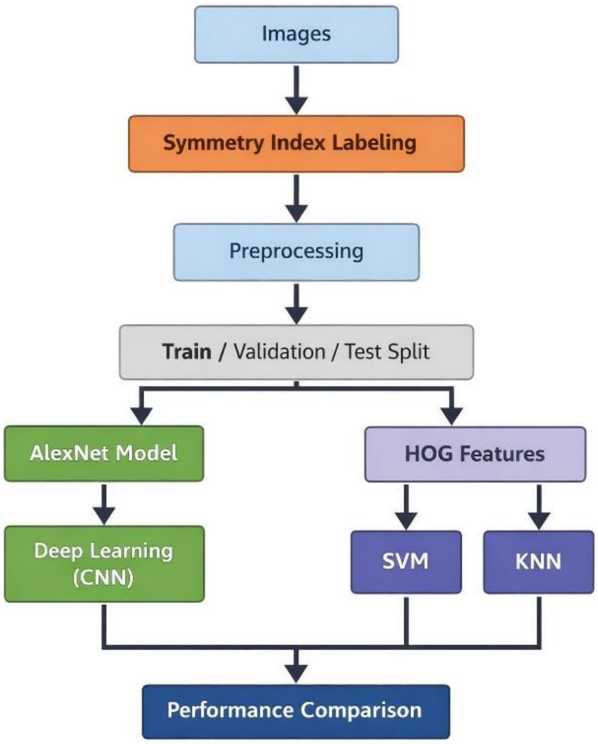

Figure 2. Overall framework of the proposed system including Symmetry Index (SI)-based labeling, preprocessing, dataset splitting, deep learning (AlexNet), and machine learning (support vector machine (SVM) and k-nearest neighbors (KNN)) for performance comparison

The first stage involves labeling the dataset images into two classes: Symmetric and Asymmetric using the proposed SI-based approach. The second stage is preprocessing, where all images are resized and standardized to ensure consistency. The third stage is dataset division, in which the dataset is split into training, validation, and testing subsets. Finally, the processed data is utilized in two parallel paths: a deep learning model based on AlexNet and traditional machine learning models (SVM and k-nearest neighbors (KNN)) for comparative analysis. The overall workflow of the proposed method is illustrated in Figure 2.

2.1 Symmetry Index–based labeling

In this stage, an automatic labeling approach based on the SI is applied to classify lumbar spine muscle images into two categories: Symmetry and Asymmetry. Each image is first converted to grayscale and resized to a uniform resolution to ensure consistency. The image is then divided vertically into left and right regions, where the right region is horizontally flipped to align with the left region.

The SI is computed by combining pixel-wise intensity differences and global statistical differences between the two regions. This is defined as [26]:

$$SI = \frac{1}{N}\sum_{i=1}^{N} |L_i - R_i| + |\mu_L - \mu_R|$$

where, L_i and R_i represent the intensity values of corresponding pixels, N is the total number of pixels, and μ_L and μ_R are the mean intensity values of the left and right regions, respectively.

A threshold-based decision rule is used to assign class labels. Images with SI values below the threshold are labeled as *Symmetry*, while those above the threshold are classified as *Asymmetry*.

2.2 Data preprocessing

In the preprocessing stage, all images are standardized to improve the consistency and performance of the models. All the images are scaled to a standard resolution in order to have the same size of input. Also, all the images are turned to grayscale to decrease the complexity of computations and do not lose the structural information needed. Moreover, the pixel intensity values are normalized to a fixed range, which aids in training models better. All these preprocessing steps are to guarantee the suitability of the dataset to the deep learning model and the traditional machine learning model.

2.3 Dataset splitting

The dataset is divided into three subsets: training, validation, and testing sets. Specifically, 70% of the data is used for training, 15% for validation, and the remaining 15% for testing. The training set is used to learn model parameters, while the validation set is used to monitor the training process and prevent overfitting.

The testing set is kept completely independent and is only used for the final evaluation of the models. This separation ensures an unbiased assessment of model performance and addresses potential data leakage issues.

2.4 Proposed deep learning model (AlexNet)

In this study, a pre-trained AlexNet model is utilized as the core deep learning architecture. Transfer learning is employed by fine-tuning the network on the labeled dataset. The final FC layers of the network are replaced to match the binary classification task. To enhance model generalization and reduce overfitting, data augmentation techniques are applied during training. These include random rotations, translations, and horizontal reflections. The network is trained using stochastic gradient descent with appropriate hyperparameters, including learning rate, batch size, and number of epochs.

This approach enables the model to automatically learn discriminative features from the data, eliminating the need for manual feature engineering.

2.5 Baseline models and comparative analysis

Two classical machine learning models are used to assess the performance of the proposed deep learning model: SVM and KNN. In these models, feature extraction is carried out using Histogram of Oriented Gradients (HOG) which is a local shape and edge information of the images. The features extracted are then used as input for training SVM and the KNN classifiers. The idea of using these baseline models is to give a fair comparison to the proposed AlexNet model. In contrast to deep learning, where features are automatically learned, traditional methods use handcrafted features, which might not be able to extract complex patterns in medical images.

3. RESULTS AND DISCUSSION

Three classification models, including SVM, KNN and the fine-tuned AlexNet deep learning model, were used to assess the performance of the proposed framework. To provide a reliable and objective assessment, the dataset was split into 70% training, 15% validation and 15% testing, which are represented in Table 1.

Table 1. Comparative analysis of classification model performance

Models	Accuracy	Precision	Recall	F1-score
AlexNet	86.27%	87.50%	84.00%	85.71%
SVM	50.98%	0.00%	0.00%	0.00%
KNN	74.51%	80.00%	64.00%	71.11%

The findings clearly show that the suggested AlexNet-based model has a high level of performance as compared to the conventional machine learning methods. SVM model was unable to correctly classify the minority group giving zero precision and recall, which implies that it does not cope with the characteristics of the data. Conversely, the KNN model performed averagely and there were significant enhancements in precision and recall as compared to SVM. The highest performance was noted in the AlexNet model, which had the highest accuracy of 86.27% and an F1-score of 85.71%. This means that deep learning methods are better able to recognize more complex patterns and subtle variations among lumbar muscle images than handcrafted feature-based methods.

The confusion matrices, (Figure 3), further point out the differences in model behavior. The SVM model has zero recall and precision on the minority class, thus classifies all the samples in one class. The KNN model had a more even distribution of classification yet there was still misclassification of both classes. Conversely, the AlexNet model demonstrated a balanced performance, being able to classify most of the symmetry and asymmetry samples correctly with a smaller number of misclassifications.

In Figure 4, the training progress of the AlexNet model reveals a gradual increase in training accuracy and constant validation performance, suggesting that the model has good generalization ability. The loss curves continually reduced throughout the training, which validated successful model convergence.

Though there were efforts to reduce the effects of class imbalance in the dataset, some effects of imbalance still exist. This is especially manifested in the performance of the traditional machine learning models and in particular the SVM which is sensitive to data distribution changes. But on the contrary, the deep learning model was more robust and stable in such cases. The suggested system has a substantial benefit since it combines an automated labeling system that is based on the SI to a deep learning-based classification model. This method is more consistent, objective and scalable, as opposed to traditional methods, which rely on either manual annotation or handcrafted geometric features extraction. Moreover, transfer learning with the adoption of the AlexNet helps to effectively extract features hierarchically even in conditions with limited information about training.

Although these are promising results, there are some limitations. Specifically, the amount of data is quite small, and it can limit the ability of the model to generalize. The future work will thus aim at increasing the diversity of datasets, imbalance of classes by using advanced data augmentation and resampling techniques and exploring more advanced deep learning models including ResNet and DenseNet that will boost performance and robustness. On the whole, the results obtained prove that the specified solution is a valid and efficient tool to use when it comes to automated lumbar muscle symmetry classification, and the obtained results are better than those of the conventional machine learning solutions.

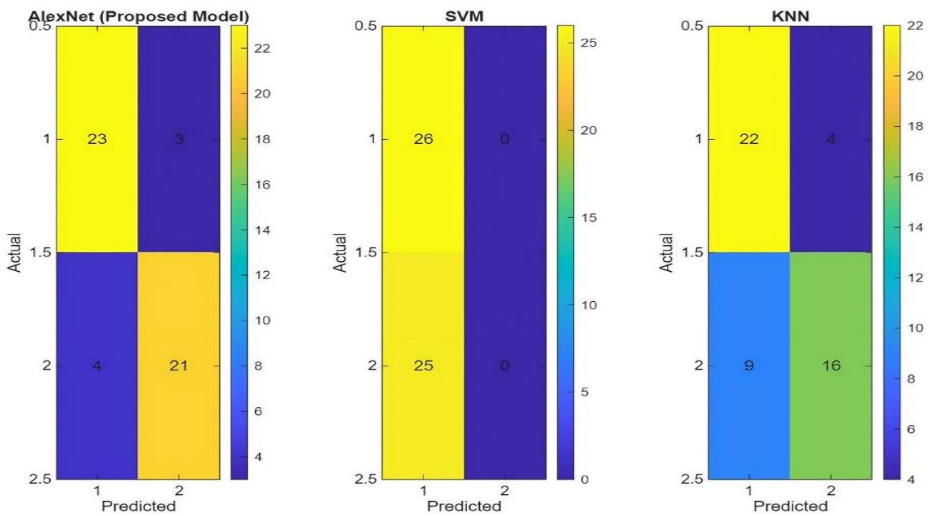

Figure 3. Confusion matrices of support vector machine (SVM), k-nearest neighbors (KNN), and AlexNet models

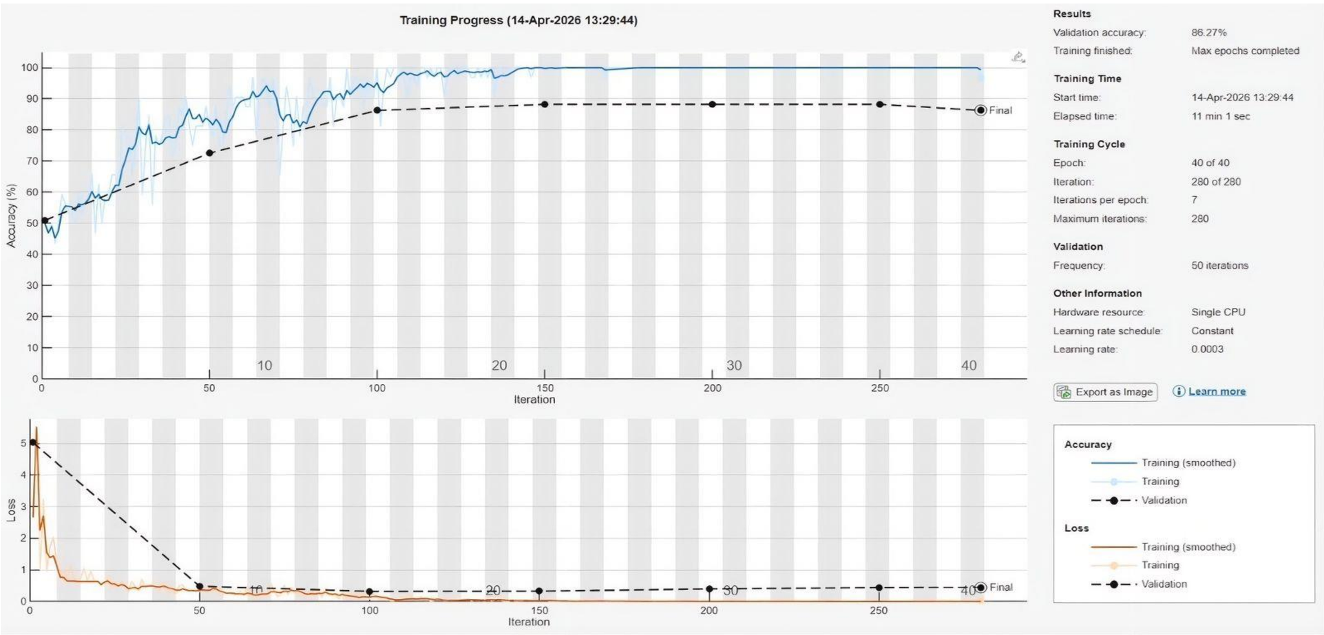

Figure 4. Training progress with AlexNet

4. CONCLUSIONS

This paper suggests a deep learning-based framework that can be used to classify lumbar spine muscle images as symmetric and asymmetric. The suggested methodology combines an automated labeling approach that relies on the SI, and, as a result, enables creation of ground-truth labels by the use of pixel-wise intensity variations between the right and left muscle regions. It should be stressed that the SI is only used to annotate data, but is not included in the training stage of the classification model and thus methodological independence of the labeling and learning is maintained. The results of the experiment show that the proposed AlexNet based model consistently outperforms the traditional machine learning classifiers, such as SVM and KNN with better performance in all measures of evaluation. The findings support the utility of deep transfer learning in extracting highly discriminative feature representations of medical imaging data, especially in symmetry related diagnostic tasks.

Despite the fact that the proposed framework has a better performance, it is limited by a few limitations that restrict its performance, mainly, the imbalance of the dataset and a small sample size, which can negatively impact the performance of generalization across underrepresented classes. Still, the suggested method, to a great extent, decreases the use of manual annotation and provides an effective and scalable solution to the medical image classification task. Future work will involve reducing the effects of class imbalance by implementing improved resampling and data augmentation methods, improving the performance of minority class recognition, and exploring more complex deep learning models like ResNet and DenseNet. Moreover, model interpretability methods will be discussed to enhance clinical relevance and support transparency in decision making.

REFERENCES

[1] Baur, D., Bieck, R., Berger, J., Neumann, J., Henkelmann, J., Neumuth, T., Heyde, C.E., Voelker, A. (2022). Analysis of the paraspinal muscle morphology of the lumbar spine using a convolutional neural network (CNN). European Spine Journal, 31: 774-782. https://doi.org/10.1007/s00586-021-07073-y

[2] van Dieën, J.H., Reeves, N.P., Kawchuk, G., van Dillen, L.R., Hodges, P.W. (2019). Motor control changes in low back pain: Divergence in presentations and mechanisms. Journal of Orthopaedic and Sports Physical Therapy, 49(6): 370-379. https://doi.org/10.2519/jospt.2019.7917

[3] Belasso, C.J., Behboodi, B., Benalim, H., Boily, M., Rivaz, H., Fortin, M. (2020). LUMINOUS database: Lumbar multifidus muscle segmentation from ultrasound images. BMC Musculoskeletal Disorders, 21: 703. https://doi.org/10.1186/s12891-020-03679-3

[4] Chris, E., Peace, P., Donald, G. (2024). Machine learning in medical imaging. ResearchGate. https://www.researchgate.net/publication/385896618_Machine_Learning_in_Medical_Imaging.

[5] Krizhevsky, A., Sutskever, I., Hinton, G.E. (2017). ImageNet classification with deep convolutional neural networks. Communications of the ACM, 60(6): 84-90. https://doi.org/10.1145/3065386

[6] Tang, W.H., Sun, J.D., Wang, S.H., Zhang, Y.D. (2023). Review of AlexNet for medical image classification. EAI Endorsed Transactions on e-Learning, 9: 1-13. https://doi.org/10.4108/eetel.4389

[7] Eldem, H., Ulker, E., Isikli, O.Y. (2023). Effects of training parameters of AlexNet architecture on wound image classification. Traitement du Signal, 40(2): 811-817. https://doi.org/10.18280/ts.400243

[8] Zhang, Y.D., Govindaraj, V.V., Tang, C.S., Zhu, W.G., Sun, J.D. (2019). High performance multiple sclerosis classification by data augmentation and AlexNet transfer learning model. Journal of Medical Imaging and Health Informatics, 9(9): 2012-2021. https://doi.org/10.1166/jmihi.2019.2692

[9] Ghazal, T.M., Munir, S., Abbas, S., Athar, A., Alrababah, H., Khan, M.A. (2023). Early detection of autism in children using transfer learning. Intelligent Automation & Soft Computing, 36(1): 11-22.

https://doi.org/10.32604/iasc.2023.030125
[10] Balashanmugam, T., Sengottaiyan, K., Kulandairaj, M. S., Dang, H. (2023). An effective model for the iris regional characteristics and classification using deep learning Alex network. IET Image Processing, 17(1): 227-238. https://doi.org/10.1049/ipr2.12630
[11] Kayadibi, I., Guraksin, G.E., Ergun, U., Suzme, N.Ö. (2022). An eye state recognition system using transfer learning: AlexNet-based deep convolutional neural network. International Journal of Computational Intelligence Systems, 15: 49. https://doi.org/10.1007/s44196-022-00108-2
[12] Li, G.M., Huang, Y.B., Chen, Z.Q., Chesser, G.D., Purswell, J.L., Linhoss, J., Zhao, Y. (2021). Practices and applications of convolutional neural network-based computer vision systems in animal farming: A review. Sensors, 21(4): 1492. https://doi.org/10.3390/s21041492
[13] Pereira, C.S., Morais, R., Reis, M.J.C.S. (2019). Deep learning techniques for grape plant species identification in natural images. Sensors, 19(22): 4850. https://doi.org/10.3390/s19224850
[14] Bu, Y.H., Jiang, X.N., Tian, J.P., Hu, X.J., Han, L.P., Huang, D., Luo, H.B. (2023). Rapid nondestructive detecting of sorghum varieties based on hyperspectral imaging and convolutional neural network. Journal of the Science of Food and Agriculture, 103(8): 3970-3983. https://doi.org/10.1002/jsfa.12344
[15] Ergun, G.B., Güney, S. (2021). Classification of canine maturity and bone fracture time based on X-ray images of long bones. IEEE Access, 9: 109004-109011. https://doi.org/10.1109/ACCESS.2021.3101040
[16] Talo, M., Yildirim, O., Baloglu, U.B., Aydin, G., Acharya, U.R. (2019). Convolutional neural networks for multi-class brain disease detection using MRI images. Computerized Medical Imaging and Graphics, 78: 101673. https://doi.org/10.1016/j.compmedimag.2019.101673
[17] Sharma, M., Patel, R.K., Garg, A., SanTan, R., Acharya, U.R. (2023). Automated detection of schizophrenia using deep learning: A review for the last decade. Physiological Measurement, 44(3): 03TR01. https://doi.org/10.1088/1361-6579/acb24d
[18] Shalbaf, A., Bagherzadeh, S., Maghsoudi, A. (2020). Transfer learning with deep convolutional neural network for automated detection of schizophrenia from EEG signals. Physical and Engineering Sciences in Medicine, 43: 1229-1239. https://doi.org/10.1007/s13246-020-00925-9
[19] Yilihamu, E.E.Y., Shang, J., Su, Z.H., Yang, J.T., Zhao, K., Zhong, H., Feng, S.Q. (2025). Quantification and classification of lumbar disc herniation on axial magnetic resonance images using deep learning models. La radiologia medica, 130: 795-804. https://doi.org/10.1007/s11547-025-01996-y
[20] Liu, Z., Hicks, Y., Sheeran, L. (2024). SpineSighter: An AI-driven approach for automatic classification of spinal function from video. Procedia Computer Science, 246: 3977-3989. https://doi.org/10.1016/j.procs.2024.09.172
[21] Hartley, T., Hicks, Y., Davies, J.L., Cazzola, D., Sheeran, L. (2024). BACK-to-MOVE: Machine learning and computer vision model automating clinical classification of non-specific low back pain for personalised management. PLoS ONE, 19(5): e0302899. https://doi.org/10.1371/journal.pone.0302899
[22] Ruchi, Singh, D., Singla, J., Rahmani, M.K.I., Ahmad, S., Rehman, M.U. (2023). Lumbar spine disease detection: Enhanced CNN model with improved classification accuracy. IEEE Access, 11: 141889-141901. https://doi.org/10.1109/ACCESS.2023.3342064
[23] Mahesh, T.R., Shrestha, P., Singh, A., Sarraf, I., Garg, R. (2022). Identification and classification of scoliosis using CNN and SVM algorithms. International Journal of Information Technology, Research and Applications (IJITRA), 1(2): 23-32. https://doi.org/10.5281/zenodo.7014436
[24] Al-Kubaisi, A., Khamiss, N.N. (2022). A transfer learning approach for lumbar spine disc state classification. Electronics, 11(1): 85. https://doi.org/10.3390/electronics11010085
[25] Mbarki, W., Bouchouicha, M., Frizzi, S., Tshibasu, F., Farhat, L.B., Sayadi, M. (2020). Lumbar spine discs classification based on deep convolutional neural networks using axial view MRI. Interdisciplinary Neurosurgery, 22: 100837. https://doi.org/10.1016/j.inat.2020.100837
[26] Gonzalez, R.C., Woods, R.E. (2018). Digital Image Processing (4th ed.). Pearson Education, New York, NY, USA.