


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



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ABSTRACT

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Accurate classification of lumbar spine muscle symmetry is essential for assessing musculoskeletal disorders, yet manual annotation remains time-consuming and subjective. This study proposes a deep learning framework that integrates automatic labeling with transfer learning for classifying lumbar muscles into symmetric and asymmetric categories. A Symmetry Index (SI) is introduced to quantify pixel-level intensity differences between left and right muscle regions, generating ground truth labels automatically without manual intervention. Notably, the SI is used exclusively for annotation and is not incorporated as a feature during model training. The proposed pipeline includes image preprocessing, intensity normalization, and dataset partitioning (70% training, 15% validation, 15% testing). A pre-trained AlexNet is fine-tuned for the binary classification task. For fair comparison, two classical machine learning models—Support Vector Machine (SVM) and K-Nearest Neighbors (KNN) with Histogram of Oriented Gradients (HOG) features—are implemented as baselines. Experimental results show that the proposed AlexNet model achieves an accuracy of 86.27%, significantly outperforming KNN (74.51%) and SVM (50.98%). The F1-scores further confirm the superiority of deep learning (85.71%) over traditional approaches (KNN: 71.11%, SVM: 0%). Confusion matrix analysis reveals that AlexNet maintains a balanced classification between symmetric and asymmetric cases, whereas SVM fails to detect the minority class entirely. These findings demonstrate that symmetry-based automatic labeling combined with transfer learning offers an effective, scalable, and annotation-efficient solution for lumbar spine muscle classification in medical imaging.

1. INTRODUCTION

Lumbar spine muscle analysis plays a critical role in the diagnosis and assessment of musculoskeletal disorders, where accurate evaluation of muscle symmetry is essential for identifying pathological conditions. However, manual assessment remains time-consuming and is often subject to inter-observer variability, which may affect diagnostic consistency and reliability.

To overcome these limitations, this study proposes a hybrid framework that integrates an automated labeling mechanism with a deep learning-based classification model. The proposed approach is designed to reduce dependence on manual annotation while maintaining high classification performance. In this framework, an automatic labeling strategy is first employed to generate ground-truth annotations, which are subsequently used to train a convolutional neural network for classification tasks.

The main contribution of this study lies in the integration of a symmetry-based automatic labeling mechanism with a deep learning framework, thereby minimizing human intervention while preserving classification accuracy. In addition, the novelty of the proposed work is reflected in the development of a scalable annotation strategy that leverages symmetry

information for label generation, combined with a transfer learning-based classification model, which enhances automation and reduces reliance on manual labeling in medical image analysis applications. Preserving the body's structural stability and overall functionality basically depending on the lumbar spine [1].

Low back pain is occurred when Any dysfunction or asymmetry in the Multifidus and Erector spinae muscles is occurred. 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, advances computational methods was used and it have led 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. In fact, the research checks Machine Learning application on multiple imaging modalities including X-ray, CT, MRI, and ultrasound, emphasizing its role in image acquisition, processing, and analysis. Disease classification, predictive modeling and tumor detection tasks, which are provided by convolutional neural networks (CNNs) and support vector machines (SVMs), can enhance early diagnosis and facilitate personalized treatment plans. With all that, challenges remain, such as improving model interpretability, addressing ethical concerns regarding patient privacy and ensuring data quality [4].

CNNs Deep learning method have provided very high performance with learning hierarchical features directly from raw imaging data. The research resulted in fact that CNNs can Accomplish high accuracy in segmenting and classifying lumbar muscles, often outperforming traditional ML approaches [1].

1.1 AlexNet

AlexNet is a convolutional neural network that has shown strong performance in image classification tasks and gained significant recognition through the ImageNet Large Scale

Visual Recognition Challenge (ILSVRC), it enables classification across 1,000 object categories and is regarded as one of the pioneering large-scale implementations 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, 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 .

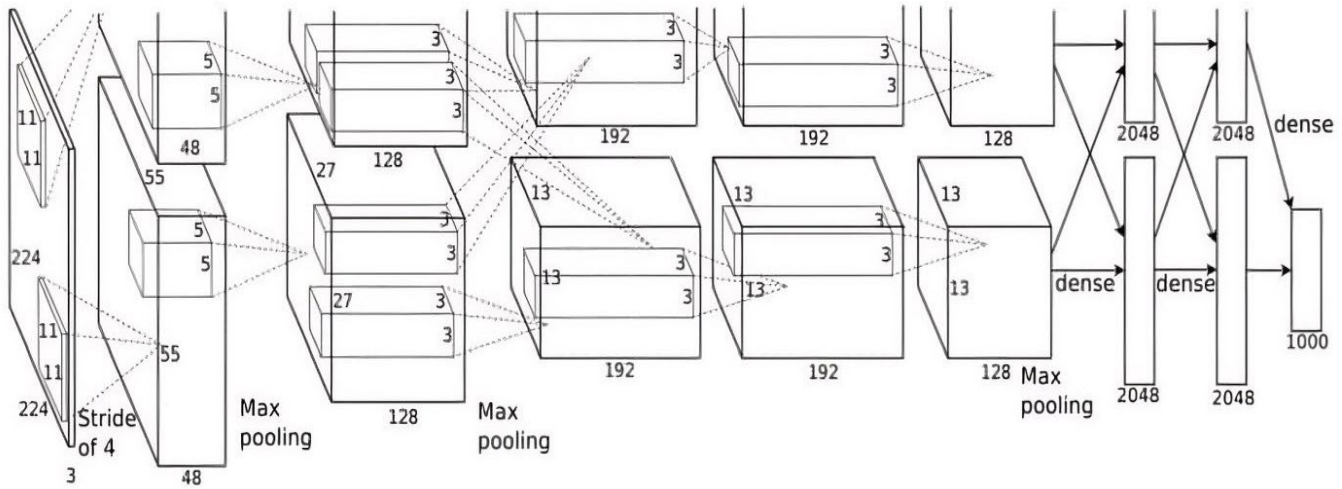


Figure 1. The architecture of AlexNet

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 ILSVRC [8], achieving superior performance over earlier approaches, 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. implemented CNNs in face recognition tasks. [9] progressed a creative transfer learning AlexNet model for the a ppearance and nonappearance detection of autism by the features of faces of children. it evolves features image of by using the pre-trained AlexNet convolutional layer. the model uses the features for training 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 [10] used AlexNet model for iris images classification, obtaining a high correct recognition rate on 163,432 iris images, providing precious premeditation for biometrics development. pre-trained AlexNet to eye condition detection is applied by Kayadibi et al. [11].

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 refined and 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) for internal validation, and 300 patients (3285 images) for external validation.

For simplification, both normal and mildly bulging discs were grouped as grades without major pathological signs, while the LDH region and severity levels were determined based on the disc–spinal canal relationship. The automated training and validation phases incorporated YOLOv8-based frameworks: YOLOv8 for object localization, YOLOv8-seg for disc segmentation, and YOLOv8-pose for anatomical keypoint estimation. The consistency and reliability of detection outcomes were evaluated using IoU, ME, precision, F1, Kappa, and 95% CI metrics.

The research by Liu et al. [20] presented “SpineSighter,” an AI-based framework designed to tailor NSLBP management by classifying patients into High Function (HF) and Low Function (LF) categories according to their spinal dynamics. Using standard video recordings integrated with computer vision algorithms, the system extracts kinematic descriptors—angular displacement, velocity, and acceleration—during serial forward flexion trials. The proposed model yielded robust classification metrics (accuracy: 95.13%, sensitivity: 93.81%, specificity: 96.00%, F1-score: 0.9442). The approach emphasizes velocity as a pivotal biomarker of spinal function, offering a foundation for advanced, patient-specific therapeutic planning.

In this research by Hartley et al. [21], a machine learning model named BACK-to-MOVE was constructed to classify NSLBP patients using expert diagnostic labels, standard video-based spinal kinematics, and PROMs. Motion data were simultaneously acquired in 2D video and 3D form during forward flexion from 83 individuals. Labeling into motor control impairment (MCI) and movement impairment (MI) was performed independently by two physiotherapists, with discrepancies resolved by a third reviewer. For pose extraction, the Higher HRNet CNN architecture was adopted, pretrained on the MS-COCO dataset and fine-tuned with feed-forward networks. Cross-validation (5-fold) confirmed strong discriminative capability (accuracy = 93.98%, sensitivity = 96.49%, specificity = 88.46%, F1 = 0.957), with pose estimation mean square error of 0.35° validating its precision against 3D standards. However, integrating PROMs features led to decreased accuracy (68.67%) and specificity (18.52%).

Ruchi et al. [22] employed optimized feature extraction and selection techniques for the detection of LSDs. A linearity-based model was utilized for feature selection, ensuring that only the most relevant features were chosen to minimize misclassification rates.

The initial stage of the study focused on data acquisition, involving both real-time image recordings and benchmark

magnetic resonance imaging (MRI) datasets. This was followed by a preprocessing stage aimed at improving data quality, where noise reduction was performed using several techniques, including median filtering, histogram equalization, normalization, and data validation procedures.

Next, background removal and region of interest (ROI) detection were conducted using a region-cut strategy. For feature extraction, a differential spider monkey optimization (SMO) algorithm was utilized to obtain optimal representations, while feature selection was performed using a convolutional neural network CNN-based model incorporating linearity constraints.

Finally, an ensemble-based classification framework was implemented for disease prediction. The proposed system was evaluated using standard performance measures, including accuracy, specificity, sensitivity, and F-score. The obtained results demonstrated strong classification performance, achieving 96% accuracy with multi support vector machine (MSVM), 94% with random forest (RF), 93.5% with decision tree (DT), and 91% with Naïve Bayes (NB), confirming the effectiveness and reliability of the proposed approach.

Mahesh et al. [23] implemented the proposed solution by processing X-ray images from both public datasets and clinical scoliosis patients. A point-based automated framework was introduced to examine multiple spinal regions, yielding reliable diagnostic results with a Convolutional Neural Network. For comparative analysis, the CNN performance was evaluated against a SVM classifier. The CNN model achieved an accuracy exceeding 90%, while the SVM achieved over 60%. Further enhancement of performance and reduction of this performance gap may be attained through improved image preprocessing, advanced feature extraction, and expansion of high-quality annotated datasets.

In the study by Al-Kubaisi et al. [24], several strategies were proposed to address the challenge of limited training data in disc state classification and to enhance the overall performance of the classification framework. Specifically, transfer learning from different datasets was investigated in combination with a newly introduced region of interest (ROI) extraction technique to improve feature relevance and model learning capability. The experimental results demonstrated that transfer learning from a source domain closely related to the target dataset yields superior performance improvements compared to generic pre-trained models. In addition, the integration of the ROI-based method further enhanced classification accuracy, resulting in performance gains of 2% for VGG19, 16% for ResNet50, 5% for MobileNetV2, and 2% for VGG16. Moreover, when compared with transfer learning from ImageNet, the proposed approach achieved additional improvements of 4% for VGG16 and 6% for VGG19, confirming the effectiveness of domain-relevant transfer learning combined with ROI-based feature refinement.

Mbarki et al. [25] developed an automated system based on deep CNNs to analyze magnetic resonance imaging (MRI) data at multiple contextual scales. The proposed approach integrates high-level feature representations to enhance the network's capability in detecting intervertebral discs in the lumbar spine. These techniques have demonstrated effectiveness and can be successfully applied to various image classification problems.

Specifically, the study employed a convolutional neural network based on the VGG16 architecture for the recognition of herniated lumbar discs in MRI scans. The trained model achieved an accuracy of 94%, indicating strong performance

and state-of-the-art capability. Overall, the proposed model is efficient and effective for the detection and diagnosis of lumbar disc herniation. The primary objective of this work is to assist radiologists in the 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.

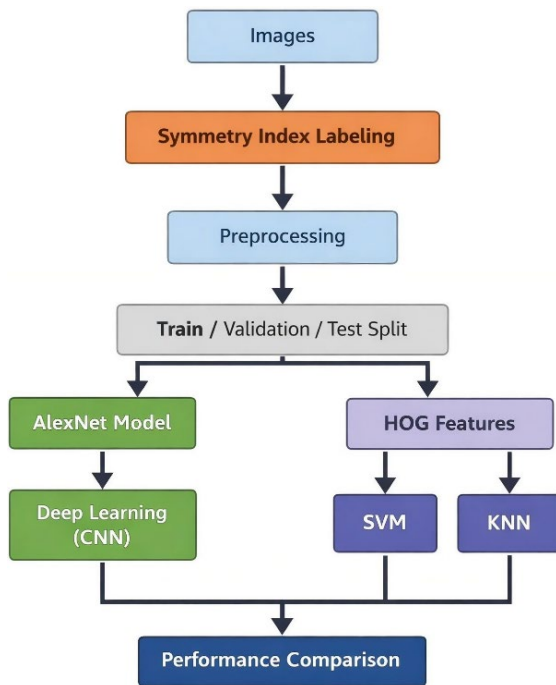


Figure 2. Overall framework of the proposed system including Symmetry Index-based labeling, preprocessing, dataset splitting, deep learning (AlexNet), and machine learning (Support Vector Machine (SVM) and K-Nearest Neighbors (KNN)) for performance comparison

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. Each image is resized to a fixed resolution to ensure uniform input dimensions. Additionally, all images are converted to grayscale to reduce computational complexity while preserving essential structural information.

Furthermore, normalization is applied to scale pixel intensity values to a consistent range, which helps improve model convergence during training. These preprocessing steps ensure that the dataset is suitable for both deep learning and traditional machine learning models.

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 fully connected 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

To evaluate the effectiveness of the proposed deep learning approach, two traditional machine learning models, SVM and KNN, are implemented as baseline methods.

For these models, feature extraction is performed using Histogram of Oriented Gradients (HOG), which captures local shape and edge information from the images. The extracted features are then used as input to train the SVM and KNN classifiers. The purpose of including these baseline models is to provide a fair comparison with the proposed AlexNet model. Unlike deep learning, which automatically learns features, traditional methods rely on handcrafted features, which may limit their ability to capture complex patterns in medical images.

3. RESULTS AND DISCUSSION

The performance of the proposed framework was evaluated using three classification models: SVM, KNN, and the fine-tuned AlexNet deep learning model. The dataset was divided into 70% training, 15% validation, and 15% testing subsets to ensure a reliable and unbiased evaluation, as illustrated 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 results clearly demonstrate that the proposed AlexNet-based model significantly outperforms the traditional machine learning approaches. The SVM model failed to correctly classify the minority class, resulting in zero precision and recall, which indicates its inability to handle the dataset characteristics effectively. In contrast, the KNN model

achieved moderate performance, with noticeable improvements in precision and recall compared to SVM.

The AlexNet model achieved the highest performance across all evaluation metrics, with an accuracy of 86.27% and an F1-score of 85.71%. This indicates that the deep learning approach is more capable of capturing complex patterns and subtle differences in lumbar muscle images compared to handcrafted feature-based methods.

The confusion matrices, as shown in Figure 3, further highlight the differences in model behavior. The SVM model classified all samples into a single class, which explains its zero recall and precision for the minority class. The KNN model demonstrated a more balanced classification but still suffered from misclassification in both classes. In contrast, the AlexNet model showed a well-balanced performance, correctly identifying most symmetry and asymmetry samples with fewer misclassifications.

The training progress of the AlexNet model, as shown in Figure 4, shows a steady increase in training accuracy and stable validation performance, indicating good generalization capability. The loss curves decreased consistently during training, confirming effective convergence of the model.

Although efforts were made to mitigate class imbalance within the dataset, residual imbalance effects remain present. This is particularly reflected in the performance of conventional machine learning models, especially the SVM, which is inherently sensitive to data distribution variations. In contrast, the deep learning model exhibited greater robustness and stability under these conditions.

The proposed framework provides a significant advantage by integrating an automated labeling mechanism based on the SI with a deep learning-based classification model. Unlike traditional methods that depend on manual annotation or handcrafted geometric feature extraction, this approach ensures greater consistency, objectivity, and scalability. Furthermore, the adoption of transfer learning using AlexNet enables effective hierarchical feature extraction, even in scenarios characterized by limited training data.

Despite these encouraging outcomes, certain limitations persist. In particular, the dataset size remains relatively limited, which may constrain the model's generalization capability. Future work will therefore focus on expanding dataset diversity, addressing class imbalance through advanced data augmentation and resampling strategies, and investigating more advanced deep learning architectures such as ResNet and DenseNet to further enhance performance and robustness.

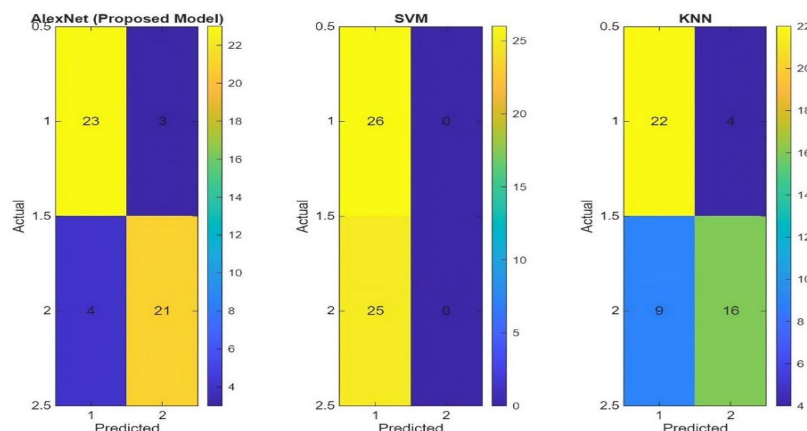


Figure 3. Confusion matrices of Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and AlexNet models

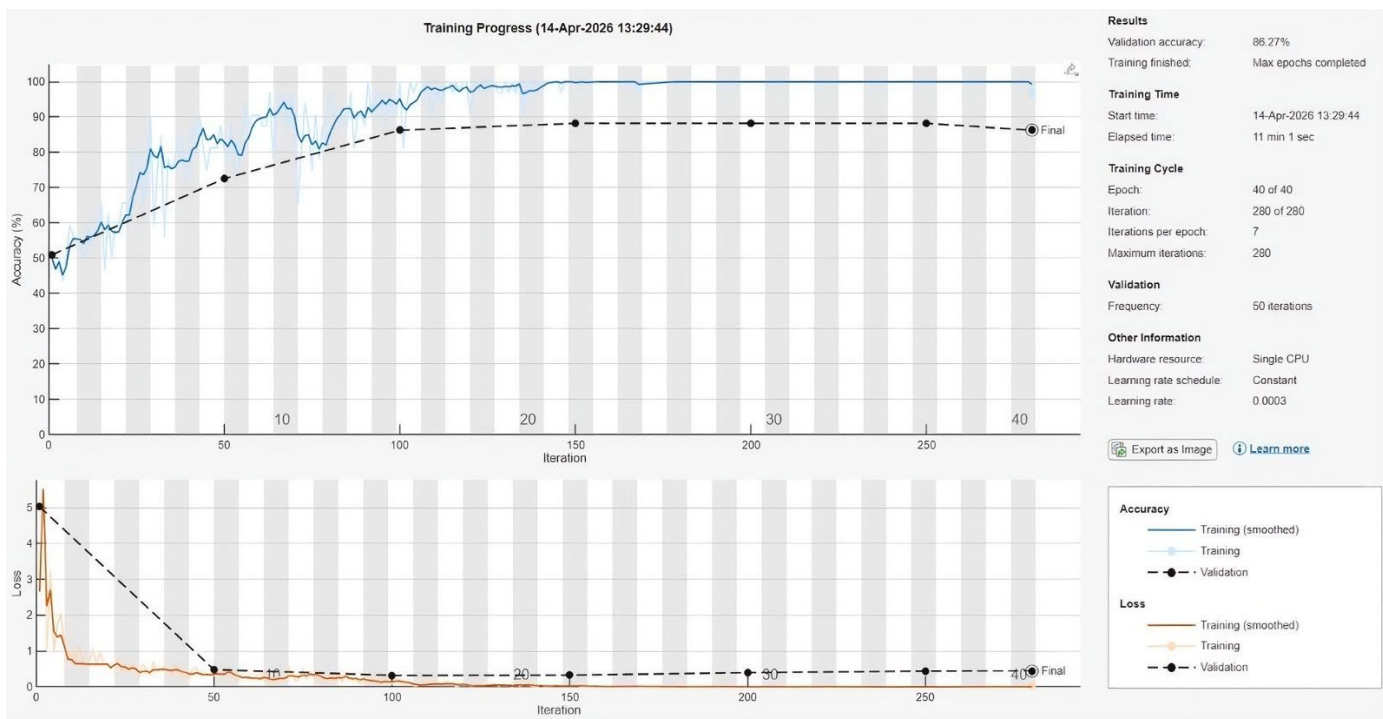


Figure 4. Training progress with AlexNet

Overall, the obtained results demonstrate that the proposed approach provides a reliable and efficient solution for automated lumbar muscle symmetry classification, achieving superior performance compared to traditional machine learning methods.

4. CONCLUSIONS

This study proposes a deep learning-based framework for the classification of lumbar spine muscle images into symmetric and asymmetric categories. The proposed methodology integrates an automated labeling strategy based on the SI, which facilitates the generation of ground-truth annotations through pixel-level intensity differences between the left and right muscle regions. It is important to emphasize that the SI is exclusively utilized for annotation purposes and is not incorporated into the training phase of the classification model, thereby ensuring methodological independence between labeling and learning processes.

The experimental findings demonstrate that the proposed AlexNet-based model consistently outperforms conventional machine learning classifiers, including SVM and KNN, achieving superior performance across evaluation metrics. These results substantiate the effectiveness of deep transfer learning in extracting highly discriminative feature representations from medical imaging data, particularly in symmetry-related diagnostic tasks.

Although the proposed framework exhibits improved performance, its effectiveness is constrained by certain limitations, primarily dataset imbalance and limited sample size, which may adversely affect generalization performance across underrepresented classes. Nevertheless, the proposed approach substantially reduces reliance on manual annotation and offers a scalable and efficient solution for medical image classification tasks.

Future research will focus on mitigating class imbalance through advanced resampling and data augmentation

strategies, enhancing minority class recognition performance, and investigating more sophisticated deep learning architectures such as ResNet and DenseNet. Furthermore, model interpretability techniques will be explored to improve clinical applicability and support transparency in decision-making processes.

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