ISSN 2442-6571

Lightweight deep learning model with ResNet14 and spatial attention for anterior cruciate ligament diagnosis

Herman [a,b,1,*], Yogan Jaya Kumar [b,2], Sek Yong Wee [b,3], Vinod Kumar Perhakaran [c,4]

[a] Faculty of Computer Science, Universitas Internasional Batam, Batam 29426, Indonesia
[b] Faculty of Artificial Intelligence and Cyber Security, Universiti Teknikal Malaysia Melaka, Melaka 76100, Malaysia
[c] M.Kandiah Faculty of Medicine & Health Sciences, Universiti Tunku Abdul Rahman, Selangor, Malaysia
[1] herman@uib.ac.id; [2] yogan@utem.edu.my; [3] ywsek@utem.edu.my; [4] vinodkumar@utar.edu.my
* corresponding author

ARTICLE INFO

Article history
Received April 4, 2025
Revised June 30, 2025
Accepted July 2, 2025
Available online July 26, 2025

Keywords
Anterior cruciate ligament
ResNet-14
Spatial attention mechanism
MRNet
Lightweight deep learning

ABSTRACT

The accuracy of diagnosing an Anterior Cruciate Ligament (ACL) tear depends on the radiologist's or surgeon's expertise, experience, and skills. In this study, we contribute to the development of an automated diagnostic model for anterior cruciate ligament (ACL) tears using a lightweight deep learning model, specifically ResNet-14, combined with a Spatial Attention mechanism to enhance diagnostic performance while conserving computational resources. The model processes knee MRI scans using a ResNet architecture, comprising a series of residual blocks and a spatial attention mechanism, to focus on the essential features in the imaging data. The methodology, which includes the training and evaluation process, was conducted using the Stanford dataset, comprising 1,370 knee MRI scans. Data augmentation techniques were also implemented to mitigate biases. The model's assessment uses performance metrics, ROC-AUC, sensitivity, and specificity. The results show that the proposed model achieved an ROC-AUC score of 0.8696, a sensitivity of 79.81%, and a specificity of 79.82%. At 6.67 MB in size, with 1,684,517 parameters, the model is significantly more compact than existing models, such as MRNet. The findings demonstrate that embedding spatial attention into a lightweight deep learning framework augments the diagnostic accuracy for ACL tears while maintaining computational efficiency. Therefore, lightweight models have the potential to enhance diagnostic capability in medical imaging, allowing them to be deployed in resource-constrained clinical settings.

1. Introduction

Generally, the diagnostic procedure for an Anterior Cruciate Ligament (ACL) tear using Magnetic Resonance Imaging (MRI) is conducted by either a radiologist or an orthopedic surgeon [1]. The professionals mentioned above are responsible for reviewing the MRI scan results. This procedure looks for signs of disruption or tearing of the ACL fibers and any associated injuries, such as bone bruising or meniscus tears [2]. MRI is indispensable in providing holistic and cleared screening for ACL tear, yet non-intrusive assessment, thereby eliminating the potential risks associated with intrusive procedures. Nevertheless, it should be noted that this procedure is not without its drawbacks. The precision of the diagnosis largely depends on the skills, experience, and competence of the radiologist or surgeon. Misreading of MRI scans occurs frequently, which is why arthroscopy is still considered the gold standard for identifying ACL tears despite being a more invasive procedure [3].

Machine learning and deep learning (DL) have emerged as a promising method for accurately determining the grades of ACL injuries [4]. The evaluation of extensive medical imaging data through machine learning algorithms has demonstrated the ability to reveal patterns that can effectively categorize ACL injury grades. Support vector machines (SVM) [5], decision trees [6], artificial neural networks (ANN) [7], and random forests [8], [9] have been proposed in recent years as machine learning techniques for classifying ACL tears. A recent study suggested the application of a deep convolutional neural network (CNN) for the automated classification of ACL tear grades through the analysis of MRI scans [10]–[12]. The CNN exhibited a high degree of accuracy and outperformed conventional diagnostic methods, thereby emphasizing the transformative potential of machine learning in grading ACL tears. However, these techniques are computationally intensive, such as CPU and GPU resources, necessitating substantial processing time and storage capacity [13]. Furthermore, the visualization tools required for interpreting the results impose an additional computational overhead during model inference, which currently restricts their practicality for routine clinical deployment [10]. The following sub-sections will discuss the lightweight deep learning model, attention mechanism, and the challenges of diagnosing ACL tear characteristics.

1.1. Lightweight Deep Learning Model

Generally, deep learning models have a complex architecture with many parameters and high computational demands. On the other hand, the lightweight deep learning model is characterized by optimizing its capability, resulting in a compact size without sacrificing its functionality [14]. Its enhanced computational efficiency enabled full functionality on devices with constrained resources, such as CPUs and GPUs [15]. The number of parameters, computational complexity, model size, and memory consumption have been commonly used as assessment measures to describe lightweight deep learning models [16]. A lightweight deep learning model is particularly well-suited for applications necessitating real-time inference [17], [18], including ACL tear diagnosis. Previous studies that have employed machine learning algorithms as an alternative to conventional medical practice for ACL tear diagnosis have all mentioned the limitation of that approach, namely the substantial computational resources required for its effective operation [19]. The lightweight model has the potential to address this limitation and can be utilized not only by major medical institutions but also by small and remote ones [20]. Thus, a lightweight model will significantly enhance accessibility for medical professionals, such as radiologists, to utilize advanced AI technologies [21].

1.2. Attention Mechanism

A fundamental aspect of deep learning techniques is the incorporation of attention mechanisms [22], which enable models to prioritize different components of an input based on their perceived significance. This mechanism enables the model to mimic human cognitive processes by focusing on multiple input aspects, producing a more comprehensive result while disregarding less significant details to eliminate superficial findings [23]. Deep learning employs this mechanism to dynamically assign importance levels, thereby ensuring optimal results are generated [24]. This assignment of dynamic significance is apparent in the graphical data analysis, as the model can concentrate on the most relevant elements of the data to produce a more thorough outcome.

1.3. ACL Tear Characteristics

Fig. 1 visually represents the ACL injury, providing context and aiding understanding of the localized focus in the MRI scans. The MRI scans of ACL tears differ significantly from other MRI scans or natural images due to their specific focus and diagnostic requirements. Fig. 2 is an example of an ACL image on an MRI scan. The highlighted area represents the ACL. These scans concentrate solely on the knee region. This selection ensures a more consistent viewpoint and angle, thereby improving the uniformity of the outcomes compared to natural images. Natural images often exhibit a considerable variation in perspective, lighting, and contextual elements; therefore, they are unreliable. Diagnosing an ACL tear primarily relies on detecting highly localized, low-level features that exhibit minimal variation across cases. This characteristic enables machine learning models designed for ACL tear detection to be lightweight and efficient. In contrast to models trained on natural images, which are constrained by the need to account for extensive variability, ACL tear detection models can focus on a more limited set of features and patterns [26]. In the context of this particular medical imaging task, this focused method decreases the computational demands of the model while increasing its precision and reliability.

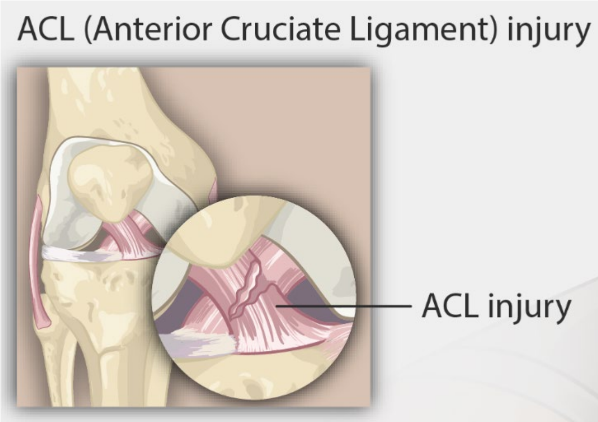

Fig. 1. Anterior Cruciate Ligament Injury. Source [25]

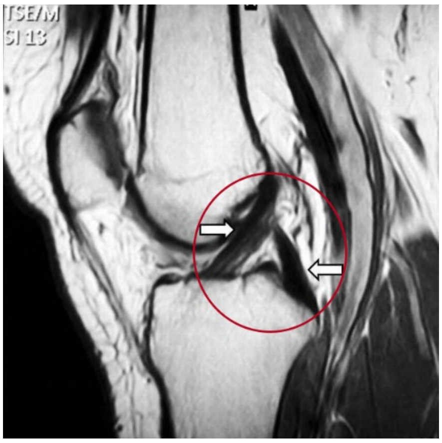

Fig. 2. ACL Tear Magnetic Resonance Imaging. Source [5]

This study contributes to the development of an automated diagnostic model for anterior cruciate ligament (ACL) tears using a novel lightweight CNN architecture enriched with spatial attention mechanisms. This approach responds to the growing call for effective and accurate diagnostic possibilities in clinical settings, where the ability to make decisions rapidly is of the essence [27], Introducing the spatial attention mechanism into the CNN framework, which can focus on high-importance features in the medical imaging data and provide better diagnostic performance without impairing computational efficiency. We demonstrate that the proposed model achieves competitive accuracy with existing deep learning models from the previous study by *Bien et al.* [28]. Our findings may help to improve computational efficiency for ACL diagnosis, which minimizes the need for invasive procedures and ultimately helps provide better outcomes for patients with ACL injuries.

2. Related Works

2.1. Models for ACL Tear Detection

Developing machine learning models for diagnosing ACL tears has garnered significant interest from academics and practitioners. Several studies have investigated various architectures to achieve this objective. For example, the research conducted by N. Bien *et al.* [28], employed a deep learning CNN model known as MRNet to convert each three-dimensional MRI series into a probability. Additionally, a feature extractor based on AlexNet was utilized for each two-dimensional slice. A study by S. S. Mazlan *et al.* [5] utilized a Support Vector Machine (SVM) architecture, which was further expanded by F. Liu *et al.* [29] using a deep learning CNN approach. A study by J. Qiao employed an Artificial Neural Network (ANN) architecture to develop a model capable of detecting a broader range of injuries while maintaining high accuracy [30]. Among the lightweight deep learning models considered for ACL Diagnosis, ResNet-18 is arguably one of the best models for this specific purpose. Despite the number of parameters in ResNet-18 being considered "Lightweight" compared to other versions of ResNet, there is a chance for improvement, which is the objective of this study.

2.2. Lightweight Deep Learning Model

The rapid expansion in both the size and complexity of deep learning models has created a significant challenge in their implementation on devices with constrained resources, such as CPUs and GPUs. In order to validate the validity of utilizing lightweight models, it is essential to ensure that a certain level of accuracy and functionality is maintained at a consistent pace. At the same time, they are being employed with minimal computational resources [31], [32]. To address this need, several techniques have been developed. For instance, a study by P. Sharma *et al.* introduced the bottleneck mechanism, which reduces the dimensionality of the input data by extracting only the most critical features before expanding the representation back to its original size, thereby significantly improving computational efficiency without compromising the model's representational power [33]. Similarly, the study by O. E. Okman *et al.* [34] employed a data-folding technique, which enhances computational power by evaluating multiple image segments simultaneously while eliminating irrelevant data.

These innovations are crucial steps toward balancing performance and efficiency in constrained resource environments. Another noteworthy advancement is group convolution, as introduced by Y. Li *et al.* [35]. This technique involves dividing a convolutional layer into multiple groups, each with its unique set of filters. By enabling parallel learning of features across these groups, the network achieves improved computational efficiency and maintains its ability to learn diverse representations. Collectively, these methods illustrate the potential for developing lightweight yet powerful models through careful architectural design and optimization techniques. However, despite the progress made, a pressing need remains for a deeper understanding of the efficiency and effectiveness of these techniques in various applications. Continued research is essential to evaluate their trade-offs and identify the optimal strategies for deploying DL models in environments with limited resources.

Structured pruning means eliminating sizable structural elements, such as whole filters or channels, directly altering the model's width. "Layer Pruning," which entails the removal of entire layers or substantial segments of layers, is included in this category since it addresses the removal of structural redundancy [16]. This study aims to evaluate layer pruning on ResNet-18 and reduce it to ResNet-14 in terms of lightweightness and effectiveness.

2.3. Attention Mechanism

The attention mechanism is a method that enables a model to focus on the most relevant parts of its input data, assigning different levels of importance to various elements, much like humans do when dealing with complex information [36]. Studies of its usage in the broader medical field are shown by L. Zhang *et al.* [37], used for detecting brain tumors, and another study by X. Zhou *et al.* [38] used an attention mechanism to detect rectal cancer. A study by C. Liang *et al.* [39] used it for ACL tear diagnosis and claimed that it improves diagnostic efficiency and reduces misdiagnosis. Nevertheless, further research is required to comprehend the utilization of this mechanism, particularly in the context of computational efficiency. The current study intends to incorporate the attention mechanism into the proposed lightweight deep learning model. We utilized the Spatial Attention Mechanism, an attention mechanism capable of distinguishing the significance of certain parts, as seen in image analysis. This new inclusion would enhance the accuracy of ResNet-18 and ResNet-14 in ACL diagnosis. Spatial attention mechanisms are mainly used because they allow a model to focus on and prioritise the most informative areas within an image or feature map, thereby improving overall performance. The Spatial Attention Mechanism method is very advantageous because spatial attention dynamically creates weights to emphasize or diminish specific regions, which is essential for minimizing the effects of noise and interference in the input data, such as fluctuations in image quality [40].

3. Method

3.1. Architecture

The proposed lightweight model takes a knee MRI scan as an input feature in this study. The ResNet architecture begins with a 7x7 convolutional that has a stride of 2, followed by batch normalization and a ReLU activation function. After this initial convolution, a max pooling operation is applied. After the initial setup, the network is divided into four main stages, each containing a series of residual blocks [41]. The quantity of blocks varies depending on the specific ResNet setup. At each stage, the dimensions of the feature maps are halved while the number of filters is increased to maintain consistent time complexity across each layer. The network culminates with a global average pooling layer followed by a fully connected layer with 1000 outputs. A softmax activation function is utilized to produce the probability distribution across the classes. Due to high accuracy, strong feature extraction, and efficient training process, ResNet-18 is well suited for MRI scan classification, which becomes a valuable tool in early disease detection [42], [43] and also the ResNet-14 model has proven to be a significant leap in the automatic detection of ACL injuries from MRI, providing a reliable early diagnosis and possibly lessening the radiologist's workload [44]. In this research, we are using ResNet-18 and ResNet-14. ResNet-14 has emerged as a lightweight deep learning model attributed to its effective architecture, balanced performance, and resource consumption. In the context of the study by C.H. Wang *et al.* [14], ResNet-14 serves as an example of the principle statement regarding model compression techniques suitable for deployment on constrained resources, such as CPU and GPU. The architecture of ResNet-14 is illustrated in Fig. 3.

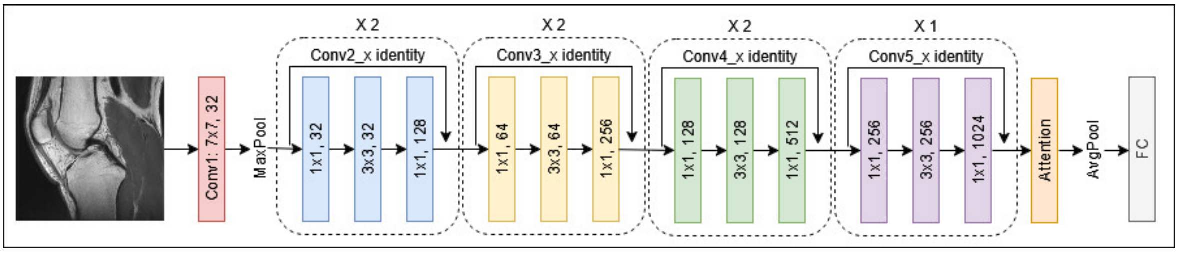

Fig. 3. ResNet-14 with Spatial Attention Mechanism Model Illustration

The attention mechanism highlights critical areas within CNN models and enhances the representation of key features. Its main objective is to improve representational power by focusing on relevant features while reducing the impact of irrelevant ones. In this paper, we present a Spatial Attention Mechanism. This mechanism gathers essential information along the spatial dimension, enabling the attention mechanism to determine what is important [45], [46]. Among other attention mechanisms, we chose the spatial attention mechanism due to its characteristics and mechanism to identify the importance of certain parts of the image by reviewing the whole image, which coincided with the objective of ACL diagnosis. As a result, our attention module efficiently aids in the distribution of information across the network by identifying what information to emphasize and what to reduce. Fig. 4 illustrates the design of the spatial attention mechanism.

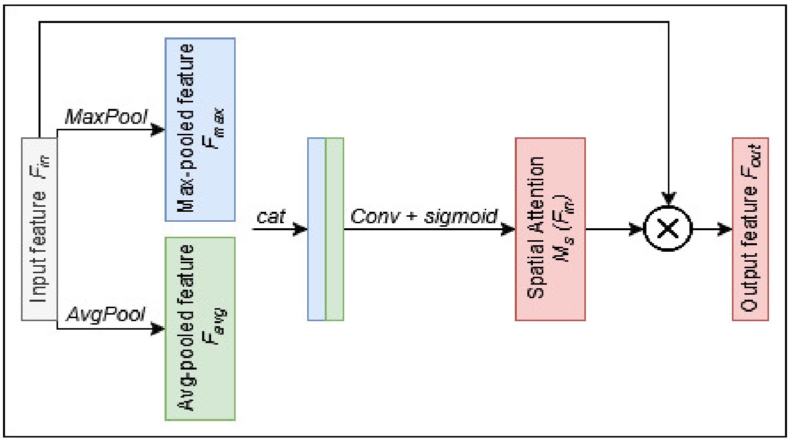

Fig. 4. Spatial Attention Mechanism Model Overview

In the spatial attention mechanism, the spatial relationships of features are leveraged to generate spatial attention maps. This component of spatial attention emphasizes the identification of significant areas. An intermediate feature map, F_{in}, of dimensions $C{\times}H{\times}W$, is processed by the spatial attention mechanism to produce a 2D spatial attention map, M_S (F_{in}), with dimensions $1{\times}H{\times}W$. The most significant spatial areas of the input feature map are highlighted in this attention map. The final output feature map, F_{out}, which maintains the exact dimensions, $C{\times}H{\times}W$, is then created by multiplying the attention map by the original feature map, F_{in}. For improved performance, this procedure assists the model in concentrating on the most pertinent portions of the input. To summarize, the procedure for acquiring an output feature map is described as follows:

$$F_{max} = MaxPool(F_{in}) \quad (1)$$

$$F_{avg} = AvgPool(F_{in}) \quad (2)$$

$$M_s(F_{in}) = \sigma\left(f^{7x7}([F_{max;}F_{avg}])\right) \quad (3)$$

$$F_{out} = F_{in} \otimes M_s(F) \quad (4)$$

In this context, $MaxPool$ denotes global max pooling; $AvgPool$ stands for global average pooling; σ indicates the sigmoid function; $f7\times7$ refers to a convolution operation with a filter size of 7×7; $\otimes$ represents element-wise multiplication.

3.2. Data

We evaluate the proposed model with Stanford datasets. The Stanford dataset consists of 1370 knee MRI scans gathered from Stanford University Medical Center during the period from January 1, 2001, to December 31, 2012 [28]. The demographic statistics of the dataset are presented in Table 1.

Table 1. Summary statistics of training and validation datasets

Statistic	Training	Validation
Number of exams	1,250	120
Age, mean (SD)	38.3 (16.9)	36.3 (16.9)
Number with abnormality (%)	913 (80.8)	95 (79.2)
Number with ACL tear (%)	208 (18.4)	54 (45.0)
Number with meniscal tear (%)	397 (35.1)	52 (43.3)
Number with ACL and meniscal tear (%)	125 (11.1)	31 (25.8)

Chronic and acute pain, postoperative evaluation or follow-up examination, injury or trauma, and other conditions were the most common indications for knee MRI scans in this dataset. The variety of different scanners used in the eventual extraction includes GE scanners (GE Discovery, GE Healthcare, Waukesha, WI) with standard knee MRI coils.

A sagittal plane MRI scan is used to show the knee from a side view, allowing either the right or left side to be visualized. The coordinate system defines the side and direction. The proposed model aims to predict the presence of ACL tears using sagittal plane MRI scans. The model generates a binary output float for the given MRI input, indicative of whether there is an “ACL tear“ or ”No ACL tear.

3.3. Training

The development of the ACL Tears Diagnostic Model followed a structured methodology, as illustrated in Fig. 5.

To prevent any potential biases during training, we apply the same data preprocessing and augmentation methods to each training instance. Data augmentation includes random horizontal flips, random rotations, and 3D affine transforms. The affine transform accomplishes three types of image distortion: scale, translation, and rotation. The Adam optimizer optimizes every model. A batch size of 5 is used, and all models are trained for 150 epochs.

Five-fold cross-validation is used to train the performance model, and we try three different learning rates: 1e-3, 1e-4, and 1e-5. We find that 1e-5 is the best learning rate for proposed models. We assess the mean and variation of performance measures using prediction outcomes from the five folds. We utilize ROC-AUC, Sensitivity, and Specificity as our key performance measures. ROC-AUC is a performance metric that assesses how effectively a classification model can differentiate between positive and negative classes [47]. Specificity measures the proportion of actual negative cases that the model correctly identifies as negative. At the same time, Sensitivity, also called recall, evaluates the proportion of actual positive cases accurately recognized by the model [48]. In addition to these, we also consider the number of parameters and model size to evaluate the model's computation complexity. The number of parameters reflects the model's complexity, and the model size indicates the memory it occupies [11].

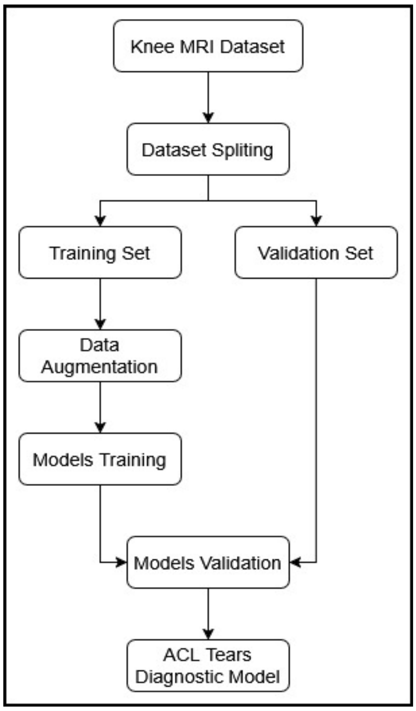

Fig. 5. ACL Tears Diagnostic Model Training and Validation Flowchart

4. Results and Discussion

Table 2 compares the diagnostic accuracy and model size of our proposed model alongside other ACL detection models. "Proposed model" refers to the configuration proposed and illustrated in Fig. 3. "Proposed Model + Spatial Attention" is developed by incorporating the "Spatial Attention Mechanism" into ResNet-14.

Table 2. Comparison of diagnostic accuracy and model size

Model	Sensitivity	Specificity	Precision	F1-score	ROC-AUC	Parameter	Model Size (mb)
ELNet	0.4615	0.9544	-	-	0.8936	211,314	0.882
MRNet+AlexNet	0.3606	0.9664	-	-	0.8822	2,469,953	46.98
ResNet-18 + Spatial Attention	0.8413	0.7722	0.7018	0.7207	0.8903	2,865,189	11.30
Proposed Model + Spatial Attention	0.7981	0.7982	0.6607	0.6727	0.8696	1,684,517	6.67
ResNet-18	0.7596	0.7961	0.5846	0.6716	0.8470	2,799,397	11.29
Proposed Model	**0.7548**	**0.7918**	**0.5488**	**0.6618**	**0.8339**	**1,618,725**	**6.66**

In this study, two models stood out as the best performers: "ELNet" and "ResNet-18 + Spatial Attention". Both models outperform all others when tested on the Stanford knee dataset. Interestingly, when we added "Spatial Attention" to the "Proposed Model," it achieved a ROC-AUC score of 0.8696 on the same dataset, while the "Proposed Model" without this feature scored 0.8339. Furthermore, the sensitivity of ResNet-18 and its counterpart with the Spatial Attention Mechanism also showed promising results, with sensitivity from 0.7596 to 0.8413. When compared with the Proposed Model with the Spatial Attention Mechanism, the improvement is more significant in terms of accuracy (0.8339 to 0.8696), sensitivity (0.7548 to 0.7981), specificity (0.7918 to 0.7982), precision (0.5488 to 0.6087), F1-score (0.6618 to 0.6829), and model size (6.66 MB to 6.67 MB) across the board show positive improvements. This indicates that "Spatial Attention" plays a crucial role in enhancing performance for both "ResNet-18" and the "Proposed Model." The results also highlight that "ResNet-18" models are highly effective and can deliver cutting-edge performance in diagnosing ACL tears. Additionally, the "Proposed Model" is much more computationally efficient; it is seven times smaller than MRNet, making it lightweight yet archiving good accuracy.

The calculated training time, illustrated in Fig. 6, can be obtained by computing the average time needed to process a total of 100 scans, incrementing by 10 as the batch size, and then dividing that total by the number of scans. ResNet-18 requires 0.0171 seconds, while ResNet-18 with Spatial Attention takes 0.0191 seconds, the proposed model takes 0.0158 seconds, and the proposed model with Spatial Attention requires 0.0181 seconds to train on a single scan. Despite the proposed model being significantly smaller than ResNet-18, we do not see notable speed enhancements compared to ResNet-18.

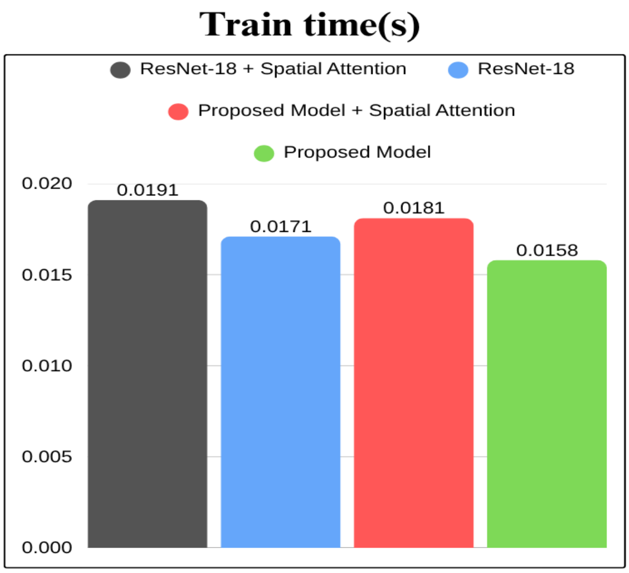

Fig. 6. Computational Speed

This study explores lightweight model architectures to optimize model size, especially in medical imaging applications when processing power may be constrained. The results show that larger models, such as "ResNet-18" and "MRNet+AlexNet," obtain excellent diagnostic accuracy at the expense of larger model sizes, which might be a significant disadvantage in contexts with limited resources.

Our "Proposed Model" using ResNet-14 architecture demonstrates that it is possible to balance model size and diagnostic performance. Its compact size makes it an attractive option for practical applications, offering a lightweight yet effective solution for diagnosing ACL tears. The increase in size when adding "Spatial Attention" further enhances its performance without significantly impacting its computational efficiency on devices with constrained resources.

The results suggest that "Spatial Attention" is a valuable addition for improving diagnostic accuracy without substantially increasing model size. This enhancement is particularly beneficial for models like the "Proposed Model," which prioritizes computationally efficient devices with constrained resources. For future work, several aspects of the study have been considered for improvement. The deployment of the proposed model will be a priority in our future work, allowing it to be applied and tested in real-life scenarios. The lightweight model operates with a single dataset, which contains 1,370 exams performed between January 1, 2001, and December 31, 2012, at Stanford University Medical Centre. This dataset will remain crucial for this study and future endeavors related to ACL tear diagnosis; it cannot possibly represent all the variations of knee and ACL tear MRI data, not to mention the variance in population demographics and timeframes. Due to the age of the dataset and the advancement of MRI Technology over the past decade, a more recent dataset should provide better insight to improve the lightweight model. We intend to update the proposed model with a newer dataset from other institutions to improve the proposed model and comprehensively recognize ACL tears.

While our lightweight model shows positive results, there is still room for improvement. A more robust attention mechanism that incorporates the latest advancements in MRI and ACL diagnostics could significantly enhance the proposed model. Additional datasets could potentially provide a more balanced representation of both positive and negative results. Weighted misclassification penalization, undersampling of negative cases, and oversampling of positive samples are further possibilities. These adjustments could help the model better handle imbalanced data and improve its performance, particularly in identifying rare or underrepresented conditions. Despite these advancements, all these models require expert judgment to interpret model results effectively. Future work should also focus on enhancing transparency, interpretability, and explainability by utilizing Explainable Artificial Intelligence (XAI) to increase the trust and confidence of end-users.

5. Conclusion

This study demonstrates the use of ResNet-14 with the newly applied Spatial Attention Mechanism to develop our lightweight model. This model can diagnose ACL tears with 86.96% accuracy, 79.81% sensitivity, and 79.82% specificity, having screened 1,684,517 parameters with a small size of 6.67 MB. The proposed model is seven times smaller than MRNet, one of the earliest studies on a model for ACL Tear Diagnosis. The findings from the present study emphasize the importance of a thorough understanding of medical imaging tasks in developing a model that is not only concise and precise but also computationally efficient.

Acknowledgment

We would like to thank the Faculty of Artificial Intelligence and Cyber Security at Universiti Teknikal Malaysia Melaka and the Faculty of Computer Science at Universitas Internasional Batam for their support of this study. The authors would like to thank Nicholas Bien *et al.* for the knee MRI dataset from https://stanfordmlgroup.github.io/projects/mrnet/.

Declarations

Author contribution. Conceptualization, Herman; Investigation, Herman, Yogan Jaya Kumar; Methodology, Herman, Yogan Jaya Kumar; Writing-original draft, Herman; Writing-review & editing, Yogan Jaya Kumar, Sek Yong Wee , Vinod Kumar Perhakaran
Funding statement. This research received no external funding.
Conflict of interest. The authors declare no conflict of interest.
Additional information. No additional information is available for this paper.

References

[1] L. Andriollo *et al.*, "The Role of Artificial Intelligence in Anterior Cruciate Ligament Injuries: Current Concepts and Future Perspectives," *Healthc.*, vol. 12, no. 3, pp. 1–16, 2024, doi: 10.3390/healthcare12030300.

[2] R. Crawford, G. Walley, S. Bridgman, and N. Maffulli, "Magnetic resonance imaging versus arthroscopy in the diagnosis of knee pathology, concentrating on meniscal lesions and ACL tears: A systematic review," *Br. Med. Bull.*, vol. 84, no. 1, pp. 5–23, 2007, doi: 10.1093/bmb/ldm022.

[3] C. Murmu, P. Tiwari, S. Sircar, and V. Agrawal, "Accuracy of magnetic resonance imaging in diagnosis of knee injuries," *Int. J. Orthop. Sci.*, vol. 3, no. 1b, pp. 85–88, 2017, doi: 10.22271/ortho.2017.v3.i1b.15.

[4] Z. Li *et al.*, "Deep Learning-Based Magnetic Resonance Imaging Image Features for Diagnosis of Anterior Cruciate Ligament Injury," *J. Healthc. Eng.*, vol. 2021, 2021, doi: 10.1155/2021/4076175.

[5] S. S. Mazlan, M. Z. Ayob, and Z. A. Kadir Bakti, "Anterior cruciate ligament (ACL) injury classification system using support vector machine (SVM)," in *2017 International Conference on Engineering Technology and Technopreneurship (ICE2T)*, Sep. 2017, no. September, pp. 1–5, doi: 10.1109/ICE2T.2017.8215960.

[6] C. I. Girard *et al.*, "Decision Tree Learning Algorithm for Classifying Knee Injury Status Using Return-to-Activity Criteria," *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. EMBS*, vol. 2020-July, pp. 5494–5497, 2020, doi: 10.1109/EMBC44109.2020.9176010.

[7] M. Martyna, W. Tomasz, G. J. Krzysztof, and G. Monika, "Artificial neural networks in knee injury risk evaluation among professional football players," in *AIP Conference Proceedings*, 2018, vol. 1922, no. February 2006, p. 070002, doi: 10.1063/1.5019069.

[8] I. Štajduhar, M. Mamula, D. Miletić, and G. Ünal, "Semi-automated detection of anterior cruciate ligament injury from MRI," *Comput. Methods Programs Biomed.*, vol. 140, pp. 151–164, 2017, doi: 10.1016/j.cmpb.2016.12.006.

[9] Q. Zhang, Y. Xiao, J. Yang, F. Deng, Z. Zhang, and J. Cai, "The value of 2D and 3D MRI texture models in Grade II and III anterior cruciate ligament injuries," *Knee*, vol. 54, no. 87, pp. 254–262, 2025, doi: 10.1016/j.knee.2025.01.007.

[10] Y. S. Jeon *et al.*, "Interpretable and Lightweight 3-D Deep Learning Model for Automated ACL Diagnosis," *IEEE J. Biomed. Heal. Informatics*, vol. 25, no. 7, pp. 2388–2397, 2021, doi: 10.1109/JBHI.2021.3081355.

[11] W. Hu and S. Razmjooy, "Combining an improved political optimizer with convolutional neural networks for accurate anterior cruciate ligament tear detection in sports injuries," *Sci. Rep.*, vol. 15, no. 1, pp. 1–14, 2025, doi: 10.1038/s41598-025-91242-2.

[12] K. Joshi and K. Suganthi, "Anterior cruciate ligament tear detection based on convolutional neural network and generative adversarial neural network," *Neural Comput. Appl.*, vol. 36, no. 9, pp. 5021–5030, 2023, doi: 10.1007/s00521-023-09350-x.

[13] J. A. J. Alsayaydeh, M. F. bin Yusof, M. Z. B. A. Halim, M. N. S. Zainudin, and S. G. Herawan, "Patient Health Monitoring System Development using ESP8266 and Arduino with IoT Platform," *Int. J. Adv. Comput. Sci. Appl.*, vol. 14, no. 4, pp. 617–624, 2023, doi: 10.14569/IJACSA.2023.0140467.

[14] C. Wang, K. Huang, and J. Chen, "Lightweight Deep Learning : An Overview," *IEEE Consum. Electron. Mag.*, vol. 13, no. August, pp. 51–64, 2024, doi: 10.1109/MCE.2022.3181759.

[15] D. Neogi, M. A. Chowdhury, M. M. Akter, and M. I. A. Hossain, "Mobile detection of cataracts with an optimised lightweight deep Edge Intelligent technique," *IET Cyber-Physical Syst. Theory Appl.*, no. July 2023, pp. 269–281, 2024, doi: 10.1049/cps2.12083.

[16] F. Chen, S. Li, J. Han, F. Ren, and Z. Yang, "Review of Lightweight Deep Convolutional Neural Networks," *Arch. Comput. Methods Eng.*, vol. 31, no. 4, pp. 1915–1937, 2024, doi: 10.1007/s11831-023-10032-z.

[17] Z. Zhu *et al.*, "Lightweight medical image segmentation network with multi-scale feature-guided fusion," *Comput. Biol. Med.*, vol. 182, no. September, p. 109204, Nov. 2024, doi: 10.1016/j.compbiomed.2024.109204.

[18] Anthony, Herman, and A. Yulianto, "Development of License Plate Recognition System Introduction Literature review," *J. Ilm. KOMPUTASI*, vol. 23, pp. 571–578, 2024. [Online]. Available at: https://ejournal.jak-stik.ac.id/index.php/komputasi/article/view/3659/900.

[19] O. Ukwandu, H. Hindy, and E. Ukwandu, "An evaluation of lightweight deep learning techniques in medical imaging for high precision COVID-19 diagnostics," *Healthc. Anal.*, vol. 2, no. August, p. 100096, 2022, doi: 10.1016/j.health.2022.100096.

[20] Z. Waheed *et al.*, "A novel lightweight deep learning based approaches for the automatic diagnosis of gastrointestinal disease using image processing and knowledge distillation techniques," *Comput. Methods Programs Biomed.*, vol. 260, no. December 2024, p. 108579, 2025, doi: 10.1016/j.cmpb.2024.108579.

[21] A. Elaraby, A. Saad, H. Elmannai, M. Alabdulhafith, M. Hadjouni, and M. Hamdi, "An approach for classification of breast cancer using lightweight deep convolution neural network," *Heliyon*, vol. 10, no. 20, p. e38524, 2024, doi: 10.1016/j.heliyon.2024.e38524.

[22] H. Kalita, S. Dandapat, and P. Kumar Bora, "Contextual Self-Attention Based UNet Architecture for Fluid Segmentation in Retinal OCT B-scans," in *Proceedings of the Fifteenth Indian Conference on Computer Vision Graphics and Image Processing*, Dec. 2024, pp. 1–8, doi: 10.1145/3702250.3702291.

[23] Y. Zhou, H. Wang, H. Jin, Y. Liu, X. Liu, and Z. Cao, "Remaining useful life prediction for machinery using multimodal interactive attention spatial–temporal networks with deep ensembles," *Expert Syst. Appl.*, vol. 263, no. September 2024, p. 125808, 2025, doi: 10.1016/j.eswa.2024.125808.

[24] J. Zhang *et al.*, "Advances in attention mechanisms for medical image segmentation," *Comput. Sci. Rev.*, vol. 56, no. December 2024, p. 100721, May 2025, doi: 10.1016/j.cosrev.2024.100721.

[25] C. Salmi, A. Lebcir, A. M. Djemmal, A. Lebcir, and N. Boubendir, "A Machine Learning Model for Automation of Ligament Injury Detection Process," in *Model and Data Engineering: 9th International Conference, MEDI 2019, Toulouse, France, October 28–31, 2019, Proceedings*, Springer, 2019, pp. 317–332, doi: 10.1007/978-3-030-32065-2_22.

[26] Y. Zuo, J. Shao, and N. Razmjooy, "Anterior cruciate ligament tear detection using gated recurrent unit and flexible fitness dependent optimizer," *Biomed. Signal Process. Control*, vol. 96, no. PB, p. 106616, 2024, doi: 10.1016/j.bspc.2024.106616.

[27] M. G. Ragab *et al.*, "A Comprehensive Systematic Review of YOLO for Medical Object Detection (2018 to 2023)," *IEEE Access*, vol. 12, no. February, pp. 57815–57836, 2024, doi: 10.1109/ACCESS.2024.3386826.

[28] N. Bien *et al.*, "Deep-learning-assisted diagnosis for knee magnetic resonance imaging: Development and retrospective validation of MRNet," *PLoS Med.*, vol. 15, no. 11, pp. 1–19, 2018, doi: 10.1371/journal.pmed.1002699.

[29] F. Liu *et al.*, "Fully Automated Diagnosis of Anterior Cruciate Ligament Tears on Knee MR Images by Using Deep Learning," *Radiol. Artif. Intell.*, vol. 1, no. 3, p. 180091, May 2019, doi: 10.1148/ryai.2019180091.

[30] J. Qiao, "The Application of Artificial Intelligence in Football Risk Prediction," *Comput. Intell. Neurosci.*, vol. 2022, pp. 1–9, Jun. 2022, doi: 10.1155/2022/6996134.

[31] M. N. Hasan, M. A. Hossain, and M. A. Rahman, "An ensemble based lightweight deep learning model for the prediction of cardiovascular diseases from electrocardiogram images," *Eng. Appl. Artif. Intell.*, vol. 141, no. December 2024, p. 109782, 2025, doi: 10.1016/j.engappai.2024.109782.

[32] H. Samma, A. S. Bin Sama, and Q. S. Hamad, "Optimized deep learning model for medical image diagnosis," *J. Eng. Res.*, no. November, pp. 1–9, Nov. 2024, doi: 10.1016/j.jer.2024.11.003.

[33] P. Sharma *et al.*, "A lightweight deep learning model for automatic segmentation and analysis of ophthalmic images," *Sci. Rep.*, vol. 12, no. 1, pp. 1–18, 2022, doi: 10.1038/s41598-022-12486-w.

[34] O. E. Okman, M. G. Ulkar, and G. S. Uyanik, "L^3U-net: Low-Latency Lightweight U-net Based Image Segmentation Model for Parallel CNN Processors," in *Proceedings of tinyML Research Symposium (tinyML Research Symposium'22)*, 2022, vol. 1, no. 1, pp. 1–6, [Online]. Available at: https://arxiv.org/abs/2203.16528.

[35] Y. Li, E. Chouzenoux, B. Charmettant, B. Benatsou, J. Lamarque, and N. Lassau, "Lightweight U-Net For Lesion Segmentation In Ultrasound Images," in *2021 IEEE 18th International Symposium on Biomedical Imaging (ISBI)*, Apr. 2021, pp. 611–615, doi: 10.1109/ISBI48211.2021.9434086.

[36] C. Lin, X. Hu, Y. Zhan, and X. Hao, "MobileNetV2 with Spatial Attention module for traffic congestion recognition in surveillance images," *Expert Syst. Appl.*, vol. 255, no. PD, p. 124701, 2024, doi: 10.1016/j.eswa.2024.124701.

[37] L. Zhang *et al.*, "A novel MRI-based deep learning networks combined with attention mechanism for predicting CDKN2A/B homozygous deletion status in IDH-mutant astrocytoma," *Eur. Radiol.*, vol. 34, no. 1, pp. 391–399, 2024, doi: 10.1007/s00330-023-09944-y.

[38] X. Zhou *et al.*, "Attention mechanism based multi-sequence MRI fusion improves prediction of response to neoadjuvant chemoradiotherapy in locally advanced rectal cancer," *Radiat. Oncol.*, vol. 18, no. 1, pp. 1–11, 2023, doi: 10.1186/s13014-023-02352-y.

[39] C. Liang *et al.*, "Effective automatic detection of anterior cruciate ligament injury using convolutional neural network with two attention mechanism modules," *BMC Med. Imaging*, vol. 23, no. 1, pp. 1–13, 2023, doi: 10.1186/s12880-023-01091-6.

[40] L. Dai, J. Liu, and Z. Ju, "Binocular Feature Fusion and Spatial Attention Mechanism Based Gaze Tracking," *IEEE Trans. Human-Machine Syst.*, vol. 52, no. 2, pp. 302–311, Apr. 2022, doi: 10.1109/THMS.2022.3145097.

[41] J. Liao *et al.*, "A machine learning-based feature extraction method for image classification using ResNet architecture," *Digit. Signal Process.*, vol. 160, no. February, p. 105036, May 2025, doi: 10.1016/j.dsp.2025.105036.

[42] M. Yang, X. Huang, L. Huang, and G. Cai, "Diagnosis of Parkinson's disease based on 3D ResNet: The frontal lobe is crucial," *Biomed. Signal Process. Control*, vol. 85, no. August 2022, p. 104904, Aug. 2023, doi: 10.1016/j.bspc.2023.104904.

[43] S. Benbakreti, M. Benouis, A. Roumane, and S. Benbakreti, "Impact of the data augmentation on the detection of brain tumor from MRI images based on CNN and pretrained models," *Multimed. Tools Appl.*, vol. 83, no. 13, pp. 39459–39478, 2024, doi: 10.1007/s11042-023-17092-0.

[44] M. Javed Awan, M. Mohd Rahim, N. Salim, M. Mohammed, B. Garcia-Zapirain, and K. Abdulkareem, "Efficient Detection of Knee Anterior Cruciate Ligament from Magnetic Resonance Imaging Using Deep Learning Approach," *Diagnostics*, vol. 11, no. 1, p. 105, Jan. 2021, doi: 10.3390/diagnostics11010105.

[45] D. Pan, J. Shen, Z. Al-Huda, and M. A. A. Al-qaness, "VcaNet: Vision Transformer with fusion channel and spatial attention module for 3D brain tumor segmentation," *Comput. Biol. Med.*, vol. 186, no. September 2024, p. 109662, 2025, doi: 10.1016/j.compbiomed.2025.109662.

[46] X. Yu *et al.*, "An improved medical image segmentation framework with Channel-Height-Width-Spatial attention module," *Eng. Appl. Artif. Intell.*, vol. 136, no. PA, p. 108751, 2024, doi: 10.1016/j.engappai.2024.108751.

[47] B. J. Erickson and F. Kitamura, "Magician's corner: 9. performance metrics for machine learning models," *Radiol. Artif. Intell.*, vol. 3, no. 3, pp. 1–7, 2021, doi: 10.1148/ryai.2021200126.

[48] J. H. Sim, N. Ma'muriyah, and A. Yulianto, "Evaluating YOLOv5 and YOLOv8 : Advancements in Human Detection," *J. Inf. Syst. Informatics*, vol. 6, no. 4, pp. 2999–3015, 2024, doi: 10.51519/journalisi.v6i4.944.