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CONTENTS

Akhmetova A.Zh., Kantureyeva M.A., Serimbetov B.A., Zhasuzakova M.Zh., Mustafayeva N.T. Identification of communities and active users in social networks.....	11
Akzhigitov D., Mukhtarkhanov M., Zhetpisbayeva A., Kulakayeva A., Zhetpisbayev K. Analysis of the mechanical structure of a 12U CubeSat nanosatellite and assessment of its mechanical stability.....	29
Alibekov A., Nurimanov A., Mukhametkali A., Kassym D., Varol H.A. Qolda-Math: a small vision-language model for mathematical reasoning in Kazakh.....	50
Alisheva S.S., Ospanova A.O., Shaimerdenova G.S., Shaimerdenova L., Zhidebayeva A.N. Detecting Kazakh language offensive comments in online content using deep learning algorithms.....	68
Askar G., Mutaikhan A., Aitkozhasyeva M., Nauryzbaikyzy G., Makhataeva Z. Retrieval beats fine-tuning: adapting a Kazakh small language model for historical question answering.....	86
Beissenova G.I., Shynzhigit B.B., Beisebayeva A.Zh., Kaldarova B.S., Lesbayev A.U. Deep neural network-based speaker authentication for secure access control systems.....	106
Bekenuly B., Baimakhanova A., Baiturganova V., Bolatbekova D. Comparison of CNN architectures for automated ACL injury classification from knee MRI.....	123
Bekbolat A., Razak A., Alimbayeva Z., Ozhikenova A. Multi-task deep learning for knee MRI pathology classification.....	139
Issakhov A., Akylbekkyzy A., Abylkassymova A. Predicting the spread of airborne viral infections in enclosed spaces.....	158
Kisseleva O., Abdramanov K., Naumenko V., Mukanova Z., Maintser D. Evaluation of serverless cold start optimization techniques.....	177
Koshkarov Ye.Zh., Amirgaliyev B.Ye., Mulesa O. Physics-aware masked pretraining for cross-basin well log foundation models.....	197
Kurmetkan T., Turysbek Zh., Mukhitova A., Nauryzbaeva A. Research on methods for reducing knowledge conflicts in large language models in Kazakh question-and-answer systems.....	214
Makatov Ye.K., Abdul Razaque, Ismukanova A.N., Salykova A.K., Glock E.S. Machine learning-based model for phishing URL detection in online social networks.....	233
Mimenbayeva A.B., Naizagarayeva A.A., Ospanova T.T., Koikelova D.K., Kudabayeva R.N. Spatial and climate data analysis for machine learning-based crop yield prediction in Northern Kazakhstan.....	255
Mukhamediev R.I., Abdoldina F.N., Gertsen Y.A. Economic opportunities and constraints of artificial intelligence adoption in Kazakhstan's resource-oriented economy.....	274

Mutanov G.M., Karyukin V.I., Ussatova O.A., Begimbayeva Y.Y., Baispay G.B. The assessment of blockchain readiness for academic document verification.....	289
Mussiraliyeva Sh., Bolatbek M., Baisylbayeva K. Classification of cyber-extremist ideologies in the Kazakh language considering multi-annotator disagreement.....	306
Omarov B.S., Sultan D.R., Rakhymberdiev D.S., Abibullayeva A.A., Toktarova A.B. Deformable attention-guided Transformer for brain tumor segmentation.....	326
Oralbekova D., Bekarystankyzy A., Yerimbetova A., Berzhanova U. Development of a streaming Kazakh speech recognition system using end-to-end models.....	346
Serek A., Shoiynbek A., Zheludkov M., Kuanyshbay D., Meraliyev B. Comparative analysis of machine learning methods for detecting fraud in text messages.....	365
Smakhanova A.K., Uskenbayeva R.K., Kassymova A.B., Kalpeyeva Zh.B., Konyrbaev N.B. Experimental research using models and methods of the university digital ecosystem.....	384
Sultanali A.E., Kazbekova G.N. Machine learning-based detection of AI-generated content in students' written works.....	401
Tashenova Zh., Yergazin A., Nurlybaeva E., Abdugulova Zh., Amanzholova Sh. Experimental evaluation of a hybrid IDPS with adaptive learning for low-latency 5G networks using edge computing.....	418
Telman D., Yerimbetova A., Daiyrbayeva E. Leakage-resistant fake news detection for Kazakh: temporal evaluation of lexical, Transformer and hybrid models.....	441
Zhanegizov A., Mamyrbayev O., Abdigappar M. Application of YOLO12 for road defect detection in GPR images.....	457

МАЗМҰНЫ

Ахметова А.Ж., Кантуреева М.А., Серимбетов Б.А., Жасұзақова М.Ж., Мұстафаева Н.Т. Әлеуметтік желілердегі қауымдастықтар мен белсенді қолданушыларды анықтау.....	11
Ақжігітов Д.Ж., Мұхтарханов М.О., Жетписбаева А.Т., Кулакаева А.Е., Жетписбаев К.У. 12U CubeSat үлгісіндегі наноспутниктің механикалық құрылымын талдау және оның механикалық орнықтылығын бағалау.....	29
Алибеков А., Нуриманов А., Мұхаметқали А., Қасым Д., Варол Х.А. Qolda-Math: қазақ тіліндегі математикалық пайымдауға арналған кіші көру-тілдік модель.....	50
Алишева С.С., Оспанова А.О., Шаймерденова Г.С., Шаймерденова Л., Жидебаева А.Н. Онлайн-контенттегі қазақ тіліндегі бейәдеп пікірлерді терең оқыту алгоритмдері арқылы анықтау.....	68
Асқар Ғ., Мұтайхан А., Айтқожаева М., Наурызбайқызы Г., Махатаева Ж. Retrieval fine-tuning-тен басым: тарихи сұрақтарға жауап беру үшін қазақша шағын тілдік модельді бейімдеу.....	86
Бейсенова Г.И., Шынжігіт Б.Б., Бейсебаева А.Ж., Қалдарова Б.С., Лесбаев А.У. Терең нейрондық желіге негізделген қауіпсіз басқару жүйелерінде сөйлеушіні аутентификациялау.....	106
Бекенұлы Б., Баймаханова А., Байтурганова В., Болатбекова Д. Алдыңғы крест тәрізді байлам жарақатын анықтауға арналған CNN архитектураларын салыстыру.....	123
Бекболат А., Разак А., Алимбаева Ж., Ожикенова А. Тізе MPT патологиясын жіктеуге арналған көп тапсырмалы терең оқыту.....	139
Исахов А.А., Ақылбекқызы А., Абылкасымова А. Шектеулі кеңістіктерде әуе тамшыларымен вирустық инфекцияның таралуын сандық модельдеу.....	158
Киселева О., Абдраманов Қ., Науменко В., Мұқанова Ж., Майнцер Д. Serverless жүйелеріндегі суық іске қосуды оңтайландыру әдістерін эксперименттік бағалау.....	177
Кошкарров Е.Ж., Амиргалиев Б.Е., Мүлеса О. Бассейнаралық ұңғымалық диаграммалардың іргелі модельдерін физикалық тұрғыдан негізделген масқаланған алдын ала оқыту.....	197
Құрметқан Т., Тұрысбек Ж., Мұхитова А., Наурызбаева А. Қазақ тіліндегі сұрақ-жауап жүйелерінде үлкен тілдік модельдердегі білім қайшылықтарын азайту әдістерін зерттеу.....	214
Мақатов Е.К., Abdul Razaque, Исмуканова А.Н., Салыкова А.К., Глюк Е.С. Онлайн әлеуметтік желілердегі фишингтік URL-дарды анықтауға арналған машиналық оқыту негізіндегі модель.....	233

Мименбаева А.Б., Найзағараева А.А., Оспанова Т.Т., Қойкелова Д.К., Қудабаева Р.Н. Солтүстік Қазақстандағы дақылдар өнімділігін машиналық оқыту арқылы болжауда кеңістіктік және климаттық деректерді талдау.....	255
Мухамедиев Р.И., Абдолдина Ф.Н., Герцен Е.А. Қазақстанның ресурстық бағытталған экономикасына жасанды интеллектті енгізудің экономикалық мүмкіндіктері мен шектеулері.....	274
Мутанов Г.М., Карюкин В.И., Усатова О.А., Бегимбаева Е.Е., Байспай Г.Б. Білім беру құжаттарының түпнұсқалығын тексеруге блокчейн технологиясының дайындығын бағалау.....	289
Мусиралиева Ш., Болатбек М., Байсылбаева К. Көпаннынотаторлы келіспеушілікті ескере отырып қазақ тіліндегі киберэкстремистік идеологияларды жіктеу.....	306
Омаров Б.С., Сұлтан Д.Р., Рахымбердиев Д.С., Абибуллаева А.А., Тоқтарова А.Б. Ми ісіктерін сегменттеуде деформацияланатын зейін механизміне негізделген мультимодальды трансформер.....	326
Оралбекова Д.О., Бекарыстанқызы А., Еримбетова А.С., Бержанова У.Г. Интегралды модельдерді қолдану арқылы қазақ тіліндегі ағындық сөйлеуді тану жүйесін әзірлеу.....	346
Серек А., Шойынбек А., Желудков М., Қуанышбай Д., Мералиев Б. Мәтіндік хабарламалардағы алаяқтықты анықтауға арналған машиналық оқыту әдістерінің салыстырмалы талдауы.....	365
Смаханова А.К., Ускенбаева Р.К., Касымова А.Б., Кальпеева Ж.Б., Қоңырбаев Н.Б. Университеттің цифрлық экожүйесінің модельдері мен әдістерін қолдана отырып жүргізілген эксперименттік зерттеу.....	384
Сұлтанәлі А.Е., Казбекова Г.Н. Білім алушылардың жазбаша жұмыстарындағы AI-контентті машиналық оқыту арқылы анықтау.....	401
Ташенова Ж.М., Ергазин Ә., Нұрлыбаева Ә.Н., Абдуғулова Ж.К., Аманжолова Ш.А. Edge Computing көмегімен төмен кідірісті 5G желілеріне арналған бейімделгіш оқытуы бар гибриді IDPS-ті эксперименттік бағалау.....	418
Тельман Д., Еримбетова А., Дайырбаева Ә. Қазақ тіліндегі жалған жаңалықтарды анықтау: лексикалық, трансформерлік және гибридті модельдерді уақыт бойынша бағалау.....	441
Жанегизов А.С., Мамырбаев Ә.Ж., Абдіғаппар М.Д. YOLO12 моделін георадар кескіндеріне қолдану.....	457

СОДЕРЖАНИЕ

Ахметова А.Ж., Кантуреева М.А., Серимбетов Б.А., Жасузакова М.Ж., Мустафаева Н.Т. Выявление сообществ и активных пользователей в социальных сетях.....	11
Акжигитов Д.Ж., Мухтарханов М.О., Жетписбаева А.Т., Кулакаева А.Е., Жетписбаев К.У. Анализ механической конструкции наноспутника модели 12U CubeSat и оценка его механической устойчивости.....	29
Алибеков А., Нуриманов А., Мухаметкали А., Касым Д., Варол Х.А. Qolda-Math: маленькая мультимодальная модель зрения и языка для математических рассуждений на казахском языке.....	50
Алишева С.С., Оспанова А.О., Шаймерденова Г.С., Шаймерденова Л., Жидебаева А.Н. Выявление оскорбительных комментариев на казахском языке в онлайн-контенте с помощью алгоритмов глубокого обучения.....	68
Аскар Г., Мутайхан А., Айткожаева М., Наурызбайкызы Г., Махатаева Ж. Retrieval эффективнее fine-tuning: адаптация малой языковой модели казахского языка для ответов на исторические вопросы.....	86
Бейсенова Г.И., Шынжигит Б.Б., Бейсебаева А.Ж., Калдарова Б.С., Лесбаев А.У. Аутентификация личности по голосу на основе глубокой нейронной сети для систем безопасного управления доступом.....	106
Бекенулы Б., Баймаханова А., Байтурганова В., Болатбекова Д. Сравнение архитектур сверточных нейронных сетей для автоматической классификации разрыва ПКС по МРТ коленного сустава.....	123
Бекболат А., Разак А., Алимбаева Ж., Ожикенова А. Многозадачное глубокое обучение для классификации патологий колена по МРТ.....	139
Исахов А.А., Акылбеккызы А., Абылкасымова А. Прогнозирование распространения вирусной инфекции воздушно-капельным путем в замкнутых помещениях.....	158
Киселева О., Абдраманов К., Науменко В., Муканова Ж., Майнцер Д. Экспериментальная оценка методов оптимизации холодного запуска в serverless-системах.....	177
Кошкарар Е.Ж., Амиргалиев Б.Е., Мулеса О. Физически-осознанное маскированное предобучение для межбассейновых фундаментальных моделей каротажных диаграмм.....	197
Курметкан Т., Турысбек Ж., Мухитова А., Наурызбаева А. Исследование методов снижения конфликтов знаний в больших языковых моделях казахских вопросно-ответных систем.....	214
Макатов Е.К., Abdul Razaque, Исмуканова А.Н., Салыкова А.К., Глок Е.С. Модель обнаружения фишинговых URL в онлайн-социальных сетях на основе машинного обучения.....	233

Мименбаева А.Б., Найзагараева А.А., Оспанова Т.Т., Койкелова Д.К., Кудабаяева Р.Н. Анализ климатических данных для прогнозирования урожайности пшеницы методами машинного обучения в Северном Казахстане.....	255
Мухамедиев Р.И., Абдолдина Ф.Н., Герцен Е.А. Экономические возможности и ограничения внедрения искусственного интеллекта в ресурсно-ориентированной экономике Казахстана.....	274
Мутанов Г.М., Карюкин В.И., Усатова О.А., Бегимбаева Е.Е., Байспай Г.Б. Оценка готовности технологии блокчейн к проверке подлинности документов об образовании.....	289
Мусиралиева Ш., Болатбек М., Байсылбаева К. Классификация киберэкстремистских идеологий на казахском языке с учетом разногласий нескольких аннотаторов.....	306
Омаров Б.С., Султан Д.Р., Рахымбердиев Д.С., Абибуллаева А.А., Токтарова А.Б. Мультимодальный трансформер на основе механизма деформируемого внимания для сегментации опухолей головного мозга.....	326
Оралбекова Д.О., Бекарыстанкызы А., Еримбетова А.С., Бержанова У.Г. Распознавание казахской речи с применением интегральных моделей.....	346
Серек А., Шойынбек А., Желудков М., Куанышбай Д., Мералиев Б. Сравнительный анализ методов машинного обучения для выявления мошенничества в текстовых сообщениях.....	365
Смаханова А.К., Ускенбаева Р.К., Касымова А.Б., Кальпеева Ж.Б., Конырбаев Н.Б. Экспериментальное исследование с использованием моделей и методов цифровой экосистемы университета.....	384
Султанали А.Е., Казбекова Г.Н. Обнаружение AI-контента в письменных работах обучающихся методами машинного обучения.....	401
Ташенова Ж.М., Ергазин А., Нурлыбаева Э.Н., Абдугулова Ж.К., Аманжолова Ш.А. Экспериментальная оценка гибридной системы обнаружения и предотвращения вторжений (IDPS) с адаптивным обучением для сетей 5G с низкой задержкой с использованием граничных вычислений.....	418
Тельман Д., Еримбетова А., Дайырбаева Э. Обнаружение фейковых новостей на казахском языке: временная оценка лексических, трансформерных и гибридных моделей.....	441
Жанегизов А.С., Мамырбаев О.Ж., Абдигаппар М.Д. Применение модели YOLOv12 для анализа данных георадара.....	457

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COMPARISON OF CNN ARCHITECTURES FOR AUTOMATED ACL INJURY CLASSIFICATION FROM KNEE MRI

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Abstract. *Relevance.* Anterior cruciate ligament (ACL) tears are among the most clinically significant knee injuries, and delayed or inaccurate diagnosis is associated with progressive joint degeneration. Magnetic resonance imaging (MRI) is the primary non-invasive modality for assessing ligament integrity, but its interpretation is time-consuming, requires considerable expertise and remains vulnerable to fatigue and cognitive bias, which motivates the development of automated decision-support tools. *Aim.* The study systematically evaluates and compares four convolutional neural network (CNN) architectures trained from scratch for three-class ACL injury classification (healthy, partial tear, complete tear). *Methods.* A publicly available dataset of 736 sagittal-plane knee MRI volumes (a subset of the KneeMRI dataset) was used. Each 3D volume was reduced to a 2D image by extracting the middle sagittal slice and resizing it to 128×128 pixels. ResNet-18, MobileNetV2, EfficientNet-B0 and MobileNetV4_small were trained end-to-end under a unified configuration with the AdamW optimizer, cosine annealing, cross-entropy loss and weighted random sampling to compensate for class imbalance. Each model was trained with five independent random seeds, and performance is reported as mean $\pm$ standard deviation of weighted precision,

recall, F1-score and AUC. *Results.* ResNet-18 achieved the best performance (F1-score 0.6637 ± 0.0351 ; AUC 0.6622 ± 0.0136), followed by EfficientNet-B0, MobileNetV4_small, and MobileNetV2. *Practical significance.* The study provides a reproducible benchmark and practical guidance for architecture selection in small-scale medical imaging tasks, showing that, when training from scratch, the input representation and the availability of pre-trained features matter more than the choice of backbone, while clinical reliability will require 3D volumetric context, pre-training and external validation.

Keywords: anterior cruciate ligament; knee MRI; convolutional neural networks; deep learning; medical image classification

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АЛДЫҢҒЫ КРЕСТ ТӘРІЗДІ БАЙЛАМ ЖАРАҚАТЫН АНЫҚТАУҒА АРНАЛҒАН CNN АРХИТЕКТУРАЛАРЫН САЛЫСТЫРУ

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Аннотация. *Өзектілігі.* Алдыңғы крест тәрізді байламның (АКБ) зақымдануы тізе буыны жарақаттарының клиникалық тұрғыдан маңызды түрлерінің бірі болып табылады. Уақтылы қойылмаған немесе дәл емес диагноз буынның үдемелі дегенерациясына әкелуі мүмкін. Магниттік-резонанстық томография (МРТ) байламдардың жағдайын бағалаудың негізгі инвазивті емес әдісі болып табылады, алайда МРТ кескіндерін талдау көп уақытты,

жоғары біліктілікті талап етеді және маманның шаршауы мен когнитивтік қателіктерінің ықпалына ұшырауы мүмкін. *Мақсаты.* АҚБ зақымдануын үш класқа - қалыпты жағдай, жартылай жыртылу және толық жыртылу - жіктеу үшін нөлден бастап оқытылған төрт конволюциялық нейрондық желі (CNN) архитектурасын жүйелі түрде бағалау және салыстыру. *Әдістері.* Сагитталды жазықтықтағы тізе буынының 736 МРТ көлемінен тұратын KneeMRI ашық деректер жиынтығы пайдаланылды. Әрбір үшөлшемді көлем орталық сагитталды кесіндіні бөліп алу арқылы екіөлшемді кескінге түрлендіріліп, 128×128 пиксель өлшеміне келтірілді. ResNet-18, MobileNetV2, EfficientNet-B0 және MobileNetV4_small модельдері AdamW оптимизаторы, косинустық оқыту жылдамдығы, кросс-энтропиялық шығын функциясы және сыныптар теңгерімсіздігін өтеуге арналған салмақталған кездейсоқ іріктеу қолданылған бірыңғай конфигурацияда оқытылды. Әр модель бес тәуелсіз кездейсоқ инициализациямен оқытылды. *Нәтижелері.* ResNet-18 ең жоғары нәтижені көрсетті: F1-score - $0,6637 \pm 0,0351$, AUC - $0,6622 \pm 0,0136$. Одан кейін EfficientNet-B0 - F1-score $0,6334 \pm 0,0457$, MobileNetV4_small - $0,6241 \pm 0,0398$ және MobileNetV2 - $0,6184 \pm 0,1095$ нәтижелерін көрсетті. *Практикалық маңыздылығы.* Зерттеу деректер көлемі шектеулі медициналық кескіндерді талдау міндеттерінде архитектураны таңдауға арналған қайталанатын эксперименттік бағдар ұсынады. Нөлден бастап оқыту жағдайында кіріс деректерін ұсыну тәсілі мен алдын ала оқытылған белгілердің қолжетімділігі базалық архитектураны таңдаудан да маңызды болуы мүмкін. Клиникалық тұрғыдан сенімді жүйелерді әзірлеу үшін үшөлшемді кеңістіктік ақпаратты пайдалану, алдын ала оқыту және сыртқы валидация қажет.

Түйін сөздер: алдыңғы крест тәрізді байлам; тізе буынының МРТ; конволюциялық нейрондық желілер; терең оқыту; медициналық кескіндерді жіктеу

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СРАВНЕНИЕ АРХИТЕКТУР СВЕРТОЧНЫХ НЕЙРОННЫХ СЕТЕЙ ДЛЯ АВТОМАТИЧЕСКОЙ КЛАССИФИКАЦИИ РАЗРЫВА ПКС ПО МРТ КОЛЕННОГО СУСТАВА

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Аннотация. *Актуальность.* Разрывы передней крестообразной связки (ПКС) относятся к числу наиболее клинически значимых травм коленного сустава, а несвоевременная или неточная диагностика может приводить к прогрессирующей дегенерации сустава. Магнитно-резонансная томография (МРТ) является основным неинвазивным методом оценки состояния связок, однако интерпретация изображений требует значительных временных затрат и высокой квалификации, а также подвержена влиянию усталости и когнитивных искажений. *Цель.* Систематически оценить и сравнить четыре архитектуры сверточных нейронных сетей (CNN), обученных с нуля, для трехклассовой классификации повреждений ПКС: норма, частичный разрыв и полный разрыв. *Методы.* Использован открытый набор данных KneeMRI, включающий 736 МРТ-объемов коленного сустава в сагиттальной плоскости. Каждый трехмерный объем преобразовывался в двумерное изображение путем извлечения центрального сагиттального среза с последующим масштабированием до 128×128 пикселей. Модели ResNet-18, MobileNetV2, EfficientNet-B0 и MobileNetV4_small обучались в единой конфигурации с использованием оптимизатора AdamW, косинусного расписания скорости обучения, функции потерь на основе кросс-энтропии и взвешенной случайной выборки для компенсации дисбаланса классов. Каждая модель обучалась с пятью независимыми случайными инициализациями. *Результаты.* Наилучший результат показала ResNet-18: F1-score - $0,6637 \pm 0,0351$, AUC - $0,6622 \pm 0,0136$. Далее следовали EfficientNet-B0 с F1-score $0,6334 \pm 0,0457$, MobileNetV4_small - $0,6241 \pm 0,0398$ и MobileNetV2 - $0,6184 \pm 0,1095$. *Практическая значимость.* Исследование предоставляет воспроизводимый ориентир для выбора архитектуры в задачах медицинской визуализации при ограниченном объеме данных. Полученные результаты показывают, что при обучении с нуля способ представления входных данных и наличие предварительно обученных признаков могут иметь большее значение, чем выбор базовой архитектуры. Для достижения клинически надежных результатов необходимо учитывать трехмерный пространственный контекст, использовать предварительное обучение и проводить внешнюю валидацию.

Ключевые слова: передняя крестообразная связка; МРТ коленного сустава; сверточные нейронные сети; глубокое обучение; классификация медицинских изображений

Introduction. The most frequently occurring injuries in sports are those involving the knee joints (Makuch et al., 2024). The knee is a particularly vulnerable structure that comprises an intricate arrangement of ligaments, menisci, and articular cartilage, which are not supposed to withstand quick turns and

rapid changes of forces, which happen to be the case in sports such as soccer and basketball (Almaawi et al., 2020; Makuch et al., 2024).

Knee injuries are usually diagnosed through physical examination and imaging (Solomon et al., 2001). Commonly, specialists start with physical tests such as the Lachman test and McMurray test (Solomon et al., 2001). While physical tests serve as a great initial screen, MRI is currently the preferred imaging method of choice for planning management of meniscal and ligament injuries due to non-invasiveness and detailed visualization of soft tissues (Qiu et al., 2023). Compared with arthroscopic detection, which is considered a gold standard of knee injury diagnosis, the accuracy of MRI in diagnosing ACL tears was as high as 90%, with a sensitivity of 95.45% and a specificity of 91.67%, which shows that results between the two methods produce consistent and comparable results. However, MRI interpretation is time-consuming and requires significant expertise, while still being vulnerable to fatigue and cognitive bias (Qiu et al., 2023; Cowen et al., 2025).

Such limitations become especially critical because, if knee injuries are not diagnosed and treated in a timely manner, they can lead to progressive joint deterioration. In many cases, patients develop osteoarthritis within ten to twenty years, resulting in chronic pain and a significant decline in quality of life (Khaleel et al., 2025). These challenges, combined with the time-consuming nature of MRI interpretation, the need for specialized expertise, and the risk of human error, highlight the need for more efficient and reliable diagnostic solutions.

Literature Review. Within this broader context, convolutional neural networks (CNNs) have become a particularly prevalent architecture for medical image analysis (Roman et al., 2025). CNNs can automatically extract meaningful features from medical images, allowing for accurate and efficient interpretation. They have been widely used for tasks including image classification, segmentation, object detection, and image reconstruction (Yu et al., 2021). In the field of knee joint pathology, DL models have been actively applied to both classification and segmentation tasks. Studies on ACL injuries, osteoarthritis, meniscal injuries, and abnormal knee appearance were found in a systematic review of 54 publications (Mead et al., 2025). Architectures such as ResNet, VGG, DenseNet, and DarkNet demonstrated excellent performance in all categories. Yeoh et al., for example, showed that shallow 3D CNNs (e.g., ResNet18 and VGG11) produced high AUC values (>0.91) for knee OA detection, suggesting their potential as clinical diagnostic tools (Yeoh et al., 2023). In terms of segmentation, combining 2D CNNs with spatial post-processing has produced high mean Dice coefficients (0.80-0.90+) in a variety of knee tissue classes, such as bone structures, cartilage, and meniscus (Ambellan et al., 2019).

However, the automated evaluation of ACL integrity poses a distinct challenge, as partial tears exhibit subtle signal changes on MRI that are difficult to distinguish from intact or fully ruptured ligaments. Regarding ACL injury classification specifically, a growing number of studies have benchmarked CNN architectures with

varying results, though the majority have framed the task as binary detection. On the MRNet dataset, Irmakci et al. compared AlexNet, ResNet-18, and GoogLeNet, reporting average AUC values of 0.8787, 0.8579, and 0.8596, respectively. Although AlexNet achieved the highest AUC, ResNet-18 outperformed the other architectures across most remaining performance metrics for ACL binary tear detection (Irmakci et al., 2019). While an earlier 2021 study using ResNet50 achieved significantly lower performance across all metrics, a later 2022 study using the Inception-v3 architecture on the same dataset reported specificity, accuracy, and sensitivity of 0.9634, 0.9542, and 0.9513, respectively (Mead et al., 2025).

Despite these advancements, most existing studies either evaluate individual architectures in isolation or restrict the task to binary classification. This not only limits direct and fair comparison between models under consistent experimental settings, but also reduces clinical applicability, as distinguishing between intact, partially torn, and fully ruptured ACLs is crucial for treatment planning.

To address these limitations, this study performs a systematic comparison of multiple CNN architectures for three-class ACL injury classification using knee MRI. Specifically, we evaluate four state-of-the-art CNN-based models under controlled experimental conditions, enabling a consistent assessment of their performance across clinically relevant categories. In addition, using the strongest of these architectures, we quantify how much of the remaining gap is attributable to the single-slice input and to the absence of pre-training.

The remainder of this paper is organized as follows. The Materials and Methods section presents the dataset, preprocessing pipeline, and network architectures. The Results section then reports the evaluation metrics and performance comparison, the Discussion situates the findings within the existing literature, and the Conclusion summarizes the study and outlines directions for future work.

Materials and methods. In this study, four distinct convolutional neural network (CNN) architectures were evaluated for automated ACL injury classification from knee MRI scans. All models were initialized randomly and trained from scratch, without the use of pre-trained weights. Each architecture was directly configured with a custom linear layer mapping the extracted high-dimensional feature spaces to the three target classes.

Knee MRI scans were first collected and preprocessed to ensure consistency in spatial resolution, intensity normalization, and input dimensionality. Each network encoded the input MRI into a high-dimensional feature representation, which was subsequently passed through a fully connected classification head to predict one of three classes: intact, partially torn, or fully ruptured ACL.

The pipeline workflow is shown in Figure 1. The framework begins with knee MRI scans as input, which are provided directly to multiple CNN architectures for feature extraction. Each CNN encoder processes the MRI data and learns hierarchical feature representations capturing structural and pathological patterns of the knee joint. The extracted features are then passed to a classification head composed of a fully connected layer, which maps the high-dimensional feature

space to class probabilities. The final output consists of three clinically relevant categories: healthy (intact ACL), partially ruptured, and fully ruptured ACL. This three-class formulation reflects the clinical grading of ACL injuries and is intended to support radiologists in making more granular and actionable diagnostic decisions.

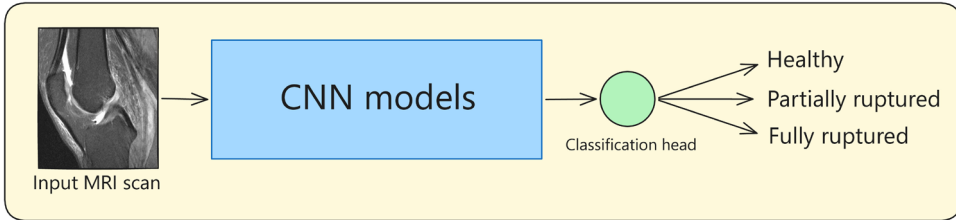


Figure 1 — The pipeline workflow

The four architectures selected for this study represent a diverse spectrum of design philosophies — from classical residual learning to compound-scaled and mobile-optimized designs — enabling a comprehensive assessment of how architectural choices affect classification performance on medical imaging data.

- **ResNet-18:** This architecture employs residual learning via skip connections to bypass non-linear transformations, effectively mitigating the vanishing gradient problem inherent in deep network optimization (He et al., 2016). For feature extraction, the terminal fully connected layer was substituted with an identity mapping, yielding a robust 512-dimensional feature representation.

- **MobileNetV2:** Engineered specifically for resource-constrained environments, MobileNetV2 leverages depthwise separable convolutions alongside inverted residual blocks and linear bottlenecks (Sandler et al., 2018). This structural design ensures highly competitive feature extraction while drastically minimizing the overall computational footprint.

- **EfficientNet-B0:** As the foundational baseline of its model family, EfficientNet-B0 utilizes a compound scaling methodology (Tan & Le, 2019). This approach uniformly optimizes network depth, width, and input resolution via a predetermined set of scaling coefficients, thereby maximizing empirical accuracy relative to computational cost.

- **MobileNetV4_small:** Compact variant of the MobileNetV4 family, MobileNetV4_small introduces the universal inverted bottleneck (UIB) block, a building block that unifies depthwise, feedforward, and optional spatial mixing operations into a one adaptable structure (Qin et al., 2024). Also, it has Mobile Multi-Query Attention (MQA), a lightweight attention mechanism that helps the model to capture global context at minimal computational cost.

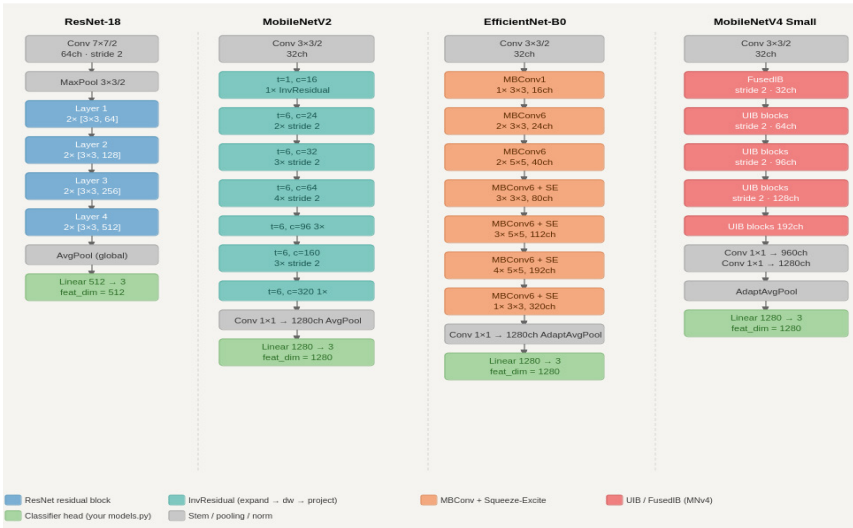


Figure 2 — Overview of the four convolutional neural network architectures evaluated in this study. Each column illustrates the full forward-pass topology of a single model — from the input stem through all feature-extraction stages to the final classification head — highlighting the distinct design philosophies underlying each architecture.

As detailed in Table 1, all models were trained for 100 epochs under a unified configuration to ensure fair and reproducible comparison across architectures. AdamW was preferred over standard Adam due to its decoupled weight decay regularization, which prevents the optimizer from conflating L2 regularization with the adaptive gradient scaling, leading to more effective regularization and improved generalization (Loshchilov & Hutter, 2017). A cosine annealing learning rate schedule was applied over the full 100 training epochs, smoothly decaying the learning rate from its initial value toward zero. The loss function used was standard cross-entropy loss, as it directly penalizes the divergence between the predicted class probability distribution and the ground truth one-hot labels. To address class imbalance, a weighted random sampler was employed during training. Class weights were computed as the inverse of the class frequency, ensuring that underrepresented classes (partial and complete tears) were sampled proportionally more often during each epoch. This strategy mitigates the risk of the model becoming biased toward the majority class, which is a common challenge in medical datasets where pathological cases are inherently less frequent than healthy ones.

Table 1 — Training Configuration for All Models.

Optimizer	Learning Rate	Weight Decay	LR Schedule	Loss Function	Class Imbalance Strategy	Epochs
AdamW	1×10^{-3}	1×10^{-4}	Cosine Annealing	Cross-Entropy	Weighted Random Sampler	1 to 100

The batch size was set to 16, reflecting the relatively small dataset size and the need to maintain stable gradient estimates during training. The entire model, encoder and classification head, was trained end-to-end without freezing any layers, allowing each architecture to fully adapt its feature representations to the MRI domain from the first training iteration.

Dataset

The KneeMRI dataset, publicly available on Kaggle (Stajduhar et al., 2017), was used in this study.

The KneeMRI dataset comprises 917 sagittal-plane MRI volumes of the knee. In this study we used the 736 volumes provided in the released archive files (vol01–vol08); the remaining cases (volumes vol09 and vol10, 181 samples) were not included in the distributed files available to us. Each usable volume is stored as a serialized 3D NumPy array (.pck format).

Each volume is annotated with one of three ACL diagnosis labels: 0 (healthy), 1 (partial tear), and 2 (complete tear). The sagittal plane was selected as it provides the most informative view for ACL assessment, allowing clear visualization of the ligament's longitudinal structure. The class distribution is inherently imbalanced, with healthy cases constituting the majority of samples, which reflects the natural prevalence of ACL conditions in clinical practice and necessitates specific strategies during both training and evaluation to prevent bias toward the majority class.

Preprocessing

Each 3D MRI volume was reduced to a 2D representation by extracting the middle slice along the sagittal axis, as this slice most reliably captures the central anatomical region of the knee joint and the longitudinal course of the ACL. The extracted slice was subsequently rescaled to the $[0, 255]$ intensity range and converted to an 8-bit grayscale image. All images were then resized to 128×128 pixels to ensure uniform input dimensionality across all model architectures.

For training, data augmentation was applied to improve model generalization and reduce overfitting, given the limited dataset size. The augmentation pipeline consisted of random horizontal flipping ($p = 0.5$), random rotation within $\pm 15^\circ$, and Gaussian blurring with a kernel size of 7 and $\sigma \in [0.1, 2.0]$. These transformations were chosen to simulate plausible variations in MRI acquisition while preserving the diagnostic integrity of the images. Finally, pixel values were normalized to the $[0, 1]$ range and standardized using a mean of 0.5 and a standard deviation of 0.5. For validation and testing, only resizing and normalization were applied, with no augmentation, to ensure unbiased evaluation on unmodified samples.

All experiments were conducted on a workstation equipped with an NVIDIA GeForce RTX 4090 GPU (CUDA 12.9). Models were implemented in Python using PyTorch and torchvision.

To ensure reproducibility and assess the stability of results across different data partitions, each model was trained five times using independent random seeds. For each seed, the dataset was partitioned into training, validation, and test sets following an 80/10/10 split, with stratified sampling applied to preserve the original

class distribution across all subsets. During training, the model checkpoint that achieved the highest weighted AUC on the validation set was retained. This best-performing checkpoint was subsequently used to evaluate final performance on the held-out test set, ensuring that reported results reflect the model's generalization ability rather than its last training state. The evaluated architectures are illustrated in Figure 2.

ResNet-18 follows the classical residual-learning paradigm: a 7×7 convolution stem with stride 2 and max-pooling, followed by four layers of paired 3×3 residual blocks that progressively double the channel width from 64 to 512, concluded by global average pooling and a fully connected layer.

MobileNetV2 employs inverted residual blocks with linear bottlenecks, in which a 1×1 expansion convolution is followed by a depthwise separable convolution and a 1×1 projection. The stem is a lightweight 3×3 convolution producing 32 channels, and subsequent stages increase channels from 16 to 320 through expansion factors of up to 6, with a final 1×1 convolution expanding to 1280 channels before average pooling and the classification head.

EfficientNet-B0 is derived via compound scaling of depth, width, and resolution. Its backbone is composed of mobile inverted bottleneck convolution (MBConv) blocks augmented with Squeeze-and-Excitation modules in the deeper stages. Channel widths progress from 16 to 320, kernel sizes alternate between 3×3 and 5×5 , and a 1×1 convolution projects to 1280 channels before adaptive average pooling and the final linear layer.

MobileNetV4 Small introduces Universal Inverted Bottleneck (UIB) blocks alongside an initial Fused Inverted Bottleneck stem. Channel widths increase from 32 to 192 across five UIB stages, followed by two consecutive 1×1 convolutions expanding to 960 and then 1280 channels, adaptive average pooling, and a linear classifier.

All classification heads (shown in green) map the final feature representation to three output classes corresponding to the ACL injury grades (healthy, partial tear, and complete tear). Color coding distinguishes block types: ResNet residual blocks (blue), inverted residual blocks (teal), MBConv blocks with Squeeze-and-Excitation (orange), UIB / FusedIB blocks (pink), classifier heads (green), and stem / pooling/normalization layers (grey).

Results

Evaluation metrics

Four main evaluation metrics were calculated on the test set to evaluate the trained models' performance: precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC). Precision (1) measures the proportion of correct positive predictions among all positive predictions made by the model, reflecting its ability to avoid false alarms. Recall (2) measures the model's capacity to correctly identify true positive instances, reflecting its sensitivity to the target condition. The F1-score (3) is computed as the harmonic mean of precision and recall, providing a single balanced measure that penalizes extreme trade-offs between the

two. Since this is a three-class problem, per-class metrics were aggregated using weighted averaging (4–6), where each class contributes proportionally to its sample count in the test set, ensuring that the reported metrics reflect performance across all classes rather than being dominated by the majority class.

AUC (8) was computed as the weighted average of per-class AUC scores (7), each measuring the area under the ROC curve for a one-vs-rest binary classification.

$$\text{Precision}_c = \frac{TP_c}{TP_c + FP_c}, \quad (1)$$

$$\text{Recall}_c = \frac{TP_c}{TP_c + FN_c}, \quad (2)$$

$$F_1 - \text{score}_c = \frac{2 \cdot \text{Precision}_c \cdot \text{Recall}_c}{\text{Precision}_c + \text{Recall}_c}, \quad (3)$$

$$\text{Precision} = \sum_{c=1}^C \frac{N_c}{N} \cdot \text{Precision}_c, \quad (4)$$

$$\text{Recall} = \sum_{c=1}^C \frac{N_c}{N} \cdot \text{Recall}_c, \quad (5)$$

$$F_1 - \text{score} = \sum_{c=1}^C \frac{N_c}{N} \cdot F_1 - \text{score}_c, \quad (6)$$

$$AUC_i = \int_0^1 TPR_i d(FPR_i), \quad (7)$$

$$\text{AUC} = \sum_{i=1}^C w_i \text{AUC}_i, \quad (8)$$

Final results for each model are reported as mean $\pm$ standard deviation across the five seeds, providing an estimate of both average performance and result stability.

Overall Performance Comparison

Table 2 summarizes the test set performance of the four CNN architectures across five independent runs. All metrics are reported as mean $\pm$ standard deviation using weighted averaging across the three classes.

Table 2 — Test set performance of CNN architectures for three-class ACL injury classification (mean $\pm$ std across 5 seeds).

Model	Parameters	Precision	Recall	F1-score	AUC
ResNet18	11.7M	0.6579 $\pm$ 0.0596	0.6892 $\pm$ 0.0287	0.6637 $\pm$ 0.0351	0.6622 $\pm$ 0.0136
MobileNetV2	3.4M	0.6653 $\pm$ 0.0503	0.6297 $\pm$ 0.1419	0.6184 $\pm$ 0.1095	0.6439 $\pm$ 0.0621
MobileNetV4 small	3.8M	0.6315 $\pm$ 0.0400	0.6379 $\pm$ 0.0778	0.6241 $\pm$ 0.0398	0.6285 $\pm$ 0.0502
EfficientNet-B0	5.3M	0.6496 $\pm$ 0.0619	0.6406 $\pm$ 0.0680	0.6334 $\pm$ 0.0457	0.5986 $\pm$ 0.1081

Overall, the results indicate moderate performance across all evaluated architectures, with no single model achieving clearly strong classification. This is consistent with the inherent difficulty of three-class ACL grading from 2D MRI slices, where distinguishing partial from complete tears relies on subtle structural differences that may not be fully captured by a single mid-sagittal slice.

Among the four architectures evaluated, ResNet-18 achieved the highest overall performance (F1-score 0.6637 ± 0.0351 ; AUC 0.6622 ± 0.0136), followed by EfficientNet-B0 (F1-score 0.6334 ± 0.0457 ; AUC 0.5986 ± 0.1081), MobileNetV4_small (F1-score 0.6241 ± 0.0398 ; AUC 0.6285 ± 0.0502), and MobileNetV2 (F1-score 0.6184 ± 0.1095 ; AUC 0.6439 ± 0.0621). MobileNetV2 exhibited the highest cross-seed variance in both recall and F1-score, with seed 42 producing an F1-score of only 0.44 due to failure to classify partial tears, while seed 12345 reached 0.73 — the highest single-seed F1-score across all architectures. EfficientNet-B0 showed the highest instability in AUC (0.43–0.70 across seeds), suggesting sensitivity to data split composition.

Discussion

The superior performance of ResNet-18 across both F1-score and AUC is consistent with the broader literature on training from scratch under data-scarce conditions. Its residual shortcut connections provide a strong inductive bias that stabilises gradient flow even with limited examples, making it less dependent on the precise weight initialisation than architectures designed primarily for scale. MobileNetV2, despite its compact 3.4M parameter count, showed the highest cross-seed variance (F1 range 0.44–0.73), indicating that its inverted-residual bottlenecks — optimised for inference efficiency — may be more sensitive to the particular class distribution in each data split when the training set is small. EfficientNet-B0 and MobileNetV4_small yielded intermediate and comparably stable results, suggesting that compound scaling and Universal Inverted Bottleneck blocks provide some regularisation benefit, though without pre-training this advantage is modest. Taken together, the spread between the four architectures (F1 0.618–0.664) is comparable to the seed-to-seed spread within a single architecture, so these rankings should be read as consistent trends rather than decisive differences. This observation motivated the additional experiments reported below, in which the input representation and the initialisation scheme — rather than the backbone — were varied.

It is also important to situate these results relative to prior work on the same KneeMRI dataset (Table 3). Štajduhar et al. (2017), who introduced the dataset, reported AUC values of 0.894 and 0.943 for partial and complete tears, respectively, using handcrafted histogram-of-oriented-gradients features aggregated across all slices together with a support vector machine. Transfer-learning approaches initialized from MRNet weights (Bien et al., 2018) and lightweight architectures such as ELNet (Tsai et al., 2020) reported still higher AUC values of approximately 0.91 and 0.96 on this dataset. These figures, however, are not directly comparable to ours: prior studies almost exclusively frame the problem as binary injury detection

(torn vs. intact), rely on ImageNet or MRNet pre-training or on handcrafted multi-slice features, and exploit the full volumetric context. In contrast, the present work addresses the substantially harder three-class grading task (healthy, partial tear, complete tear), trains all networks from scratch, and reduces each volume to a single mid-sagittal 128×128 slice. The lower absolute AUC obtained here (≈ 0.66 for the best model) therefore reflects the increased task difficulty and the deliberately constrained input and training regime rather than an inferior modelling approach, and it underscores the value of pre-training and multi-slice context as immediate directions for improvement. To the best of our knowledge, no directly comparable three-class benchmark on this dataset has been reported, which is the specific gap addressed by this comparative study.

Table 3 — Reported AUC of prior published methods on the KneeMRI (Štajduhar et al., 2017) dataset compared with the present study. Prior results address a different (binary) task and use pre-training or handcrafted multi-slice features, and are therefore not directly comparable.

Study	Method	Task	Reported AUC
Štajduhar et al. (2017)	HOG features + SVM, all slices	Binary (injury detection)	0.894 / 0.943 (partial / complete)
Bien et al. (2018)	CNN, MRNet transfer learning	Binary detection	≈ 0.91
Isai et al. (2020), ELNet	Lightweight CNN	Binary detection	0.96
This work	ResNet-18, from scratch, single slice	Three-class grading	0.66 (best: ResNet-18)

Multi-slice input and pretraining. Beyond the single-slice, from-scratch setting used for the architecture comparison above, we further evaluated ResNet-18 with a multi-slice (2.5D) input and with ImageNet pretraining (Table 4). Replacing the single central slice with an aggregation of five central slices raised the AUC from 0.662 to 0.673, and combining the multi-slice input with ImageNet pretraining increased it further to 0.782, together with an F1-score of 0.713. This improvement over the single-slice, from-scratch configuration was consistent across all five random seeds (paired t-test, $p = 0.022$).

Table 4 — Effect of multi-slice input and ImageNet pretraining for ResNet-18 (five seeds, mean $\pm$ std).

Configuration	Precision	Recall	F1-score	AUC
ResNet-18 (single slice)	0.6579 $\pm$ 0.0596	0.6892 $\pm$ 0.0287	0.6637 $\pm$ 0.0351	0.6622 $\pm$ 0.0136
ResNet-18 + multi-slice (5 slices)	0.6643 $\pm$ 0.0631	0.6108 $\pm$ 0.1309	0.6199 $\pm$ 0.1051	0.6733 $\pm$ 0.0568
ResNet-18 + pretraining + multi-slice	0.7006 $\pm$ 0.0444	0.7432 $\pm$ 0.0226	0.7132 $\pm$ 0.0344	0.7816 $\pm$ 0.0761

This ablation was deliberately restricted to ResNet-18, the strongest architecture in the from-scratch comparison, in order to isolate the effect of the input

representation and the initialisation scheme from the effect of the architecture itself. The consistency of the gain across all five seeds indicates that the limiting factor in the from-scratch setting is the information available at the input and the absence of pre-trained features, rather than the choice among the four backbones compared above.

It should be emphasised that the absolute AUC values obtained here remain moderate, which is expected for several reasons. First, unlike most prior work on this dataset, which frames ACL assessment as a binary task (torn vs. intact), we address the harder three-class problem of distinguishing healthy, partial, and complete tears. Second, the dataset is severely imbalanced: complete tears account for only a small fraction of the samples (four cases in each held-out test set), which makes this class particularly difficult to learn and to evaluate reliably. Third, the weighted metrics are dominated by the majority healthy class and therefore give only a coarse view of performance on the clinically important injury classes. Together, these factors explain why the absolute scores are lower than the binary AUCs of 0.9 and above reported elsewhere, and they indicate that larger, more balanced data and richer volumetric context are the most promising directions for improvement.

This study has several limitations.

The dataset used here is small (736 volumes; the vol09–vol10 files of the full 917-volume KneeMRI release were not available to us) and highly imbalanced, with healthy cases dominating.

Although weighted sampling was applied, minority classes remained underrepresented, likely contributing to moderate performance and variability in precision–recall trade-offs. With larger or more balanced datasets, the relative ranking of architectures may change. Furthermore, reducing each 3D MRI volume to a single 2D mid-sagittal slice, while computationally efficient and consistent with prior work, inevitably discards spatial information along the depth axis that could be diagnostically valuable for distinguishing between injury grades. The ACL is a three-dimensional structure, and its integrity may be more accurately assessed by considering the full volumetric context rather than a single representative slice. Future work should explore 3D CNN architectures or multi-slice aggregation strategies that preserve this spatial information while remaining tractable under limited data conditions. Finally, the held-out test set contains only 74 cases per seed, of which four are complete tears, so the confidence intervals on all reported metrics are wide; the comparisons should therefore be read as consistent trends rather than definitive rankings.

The findings of this study, while informative as a comparative benchmark of CNN architectures under constrained conditions, should be interpreted with appropriate caution. The relatively small and single-source dataset limits the generalizability of the conclusions to larger and more diverse clinical populations. External validation on independent cohorts from different imaging centers and scanner protocols is required before real-world deployment. Given that the absolute performance of all

models remains close to the lower bound of usefulness ($AUC \approx 0.60$ – 0.66), these models are not yet suitable for clinical decision support and should be regarded only as a methodological benchmark; substantial gains in accuracy, together with external validation, are required before any clinical use is considered.

Conclusion

This study evaluated four CNN architectures for automated three-class ACL injury classification from knee MRI scans, trained from scratch under a unified experimental setup. The results show that, under these constrained conditions, differences between the four backbones are small relative to the seed-to-seed variability, indicating that the choice of architecture is not the dominant factor in this setting. ResNet-18 achieved the highest overall F1-score and AUC, and also proved the most stable across random seeds, whereas MobileNetV2 showed the widest spread in F1-score, a property that matters when only a small training set is available. While dataset size, class imbalance, and the reduction of 3D volumes to a single 2D slice limit the generalizability of these findings, this work provides a reproducible benchmark for ACL classification under realistic data constraints and offers practical guidance on architecture selection for similar small-scale medical imaging tasks. Future work should explore 3D architectures, transfer learning, and external validation on larger and more diverse cohorts to move toward clinically deployable AI-assisted ACL assessment. A controlled ablation on ResNet-18 supports this direction: combining a multi-slice input with ImageNet pre-training raises the AUC from 0.66 to 0.78 and the F1-score from 0.66 to 0.71, a larger gain than any difference observed between the four architectures trained from scratch.

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