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MULTI-TASK DEEP LEARNING FOR KNEE MRI PATHOLOGY CLASSIFICATION

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Abstract. Magnetic resonance imaging (MRI) is the primary non-invasive modality for diagnosing internal knee derangement, but manual reading of multi-planar examinations is time-consuming and subject to inter-observer variability, particularly for anterior cruciate ligament (ACL) and meniscus tears. Most deep learning approaches train a separate single-task model for each pathology, which limits the use of shared anatomical representations and complicates deployment. This study develops and evaluates a unified multi-task, multi-view framework that classifies three knee pathologies from multi-plane MRI in a single forward pass. Using the public part of the MRNet dataset (1,250 examinations with axial, coronal and sagittal series), we designed Multi-View Multi-Task MRNet (MVMT-MRNet), in which one ResNet50 backbone shared by all planes encodes each plane, slice features are max-pooled, and a late-fusion module feeds three classification heads. The 120 public validation examinations served as the held-out test set. Training used augmentation, class-weighted binary cross-entropy, mixed precision and gradient accumulation over eight examinations with a learning rate of 8×10^{-5}, selected on validation data. On the test set the multi-task model reached AUCs of 0.844 (95% CI 0.752–0.922) for abnormality, 0.914

(0.857–0.959) for ACL tear and 0.664 (0.567–0.757) for meniscus tear, a mean of 0.807 (0.749–0.860). Three single-task models of identical architecture reached a mean AUC of 0.853 (0.802–0.897); the paired difference of −0.046 (−0.115 to +0.015) includes zero, but the multi-task model was significantly worse for meniscus tear (−0.126, −0.231 to −0.020). Averaging gradients over eight examinations helped only when the learning rate was scaled accordingly. A single shared model (25.3 M parameters instead of 75.8 M, one forward pass instead of three), trainable on one consumer GPU, thus matches three single-task models on mean AUC, but parameter sharing redistributes accuracy across tasks rather than adding it. External validation is required before clinical use. Code: https://github.com/Amanekkkk/MRNet_multihead.

Key words: knee MRI, multi-task learning, ResNet50, pathology classification, AUC, MRNet.

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ТІЗЕ МРТ ПАТОЛОГИЯСЫН ЖІКТЕУГЕ АРНАЛҒАН КӨП ТАПСЫРМАЛЫ ТЕРЕҢ ОҚЫТУ

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Аннотация. Магнитті-резонанстық томография (МРТ) тізе буынының ішкі зақымдануларын анықтаудың негізгі инвазивті емес әдісі, алайда көп

проекциялы суреттерді қолмен талдау көп уақытты қажет етеді және әсіресе алдыңғы крест тәрізді байлам (АКБ) мен мениск жыртылуларында мамандар арасында сәйкессіздік туындатады. Қолданыстағы тәсілдердің көпшілігі әр патология үшін жеке модель қолданады, бұл ортақ анатомиялық белгілерді пайдалануды шектейді. Зерттеудің мақсаты – тізенің үш патологиясын бір өтуде бір мезгілде жіктейтін көп тапсырмалы, көп проекциялы терең оқыту моделін әзірлеу және бағалау. MRNet деректер жиынтығының ашық бөлігінде (1250 зерттеу; аксиальды, корональды және сагиттальды проекциялар) MVMT-MRNet архитектурасы әзірленді: үш проекцияға ортақ бір ResNet50 желісі әр проекцияны өңдейді, кесінді белгілері максималды пулинг арқылы біріктіріледі, ал кейінгі біріктіру модулі нәтижені үш классификациялық басқа береді. 120 зерттеуден тұратын ашық валидациялық жиын тест жиыны ретінде қолданылды. Оқыту аугментациямен, кластар бойынша өлшемделген шығын функциясымен, аралас дәлдікпен және градиенттерді сегіз зерттеу бойынша жинақтаумен (оқыту жылдамдығы 8×10^{-5}) жүргізілді. Тест жиынында көп тапсырмалы модель жалпы патологияда AUC 0,844 (95% CA 0,752–0,922), АКБ жыртылуында 0,914 (0,857–0,959), мениск жыртылуында 0,664 (0,567–0,757) көрсетті; орташа AUC 0,807 (0,749–0,860) құрады. Архитектурасы бірдей үш бір тапсырмалы модельдің орташа AUC мәні 0,853 (0,802–0,897); жұптық айырма −0,046 (−0,115…+0,015) нөлді қамтиды, бірақ мениск жыртылуында көп тапсырмалы модель статистикалық мәнді түрде нашар болды (−0,126; −0,231…−0,020). Осылайша, бір тұтынушылық GPU-да оқытылатын ортақ бір модель (75,8 млн орнына 25,3 млн параметр, үш өтудің орнына бір өту) орташа AUC бойынша үш модельден ерекшеленбейді, алайда параметрлерді ортақ пайдалану дәлдікті арттырмай, оны тапсырмалар арасында қайта бөледі. Клиникалық қолданысқа дейін сыртқы валидация қажет. Код: https://github.com/Amanekkkk/MRNet_multihead.

Түйін сөздер: тізе МРТ, көп тапсырмалы оқыту, ResNet50, патологияны жіктеу, AUC, MRNet.

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МНОГОЗАДАЧНОЕ ГЛУБОКОЕ ОБУЧЕНИЕ ДЛЯ КЛАССИФИКАЦИИ ПАТОЛОГИЙ КОЛЕНА ПО МРТ

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Аннотация. *Актуальность***.** Магнитно-резонансная томография (МРТ) является основным неинвазивным методом диагностики внутренних повреждений коленного сустава, однако ручной анализ многопроекционных снимков трудоёмок и вариабелен между специалистами, особенно при разрывах передней крестообразной связки (ПКС) и мениска. Большинство подходов используют отдельную модель для каждой патологии, что ограничивает использование общих анатомических признаков. *Цель***.** Разработать и оценить единую многозадачную многопроекционную модель глубокого обучения, классифицирующую три патологии колена по МРТ за один проход. *Методы***.** На общедоступной части набора данных MRNet (1250 исследований; аксиальная, корональная и сагиттальная проекции) разработана архитектура MVMT-MRNet: общий для трёх проекций магистральный модуль ResNet50 кодирует каждую проекцию, признаки срезов агрегируются максимальным пулингом, а модуль позднего слияния передаёт представление трём классификационным головкам. Открытая валидационная выборка из 120 исследований использована как тестовая. Обучение включало аугментацию, взвешенную по классам функцию потерь, смешанную точность и накопление градиентов по восьми исследованиям при скорости обучения 8×10^{-5}. Модель сравнивалась с тремя однозадачными моделями идентичной архитектуры. *Результаты***.** На тестовой выборке многозадачная модель достигла AUC 0,844 (95% ДИ 0,752–0,922) при выявлении общей патологии, 0,914 (0,857–0,959) при разрыве ПКС и 0,664 (0,567–0,757) при разрыве мениска; средний AUC составил 0,807 (0,749–0,860). Однозадачные модели дали средний AUC 0,853 (0,802–0,897); парная разность −0,046 (−0,115…+0,015) включает ноль, однако при разрыве мениска многозадачная модель статистически значимо хуже (−0,126; −0,231…−0,020). *Практическая значимость***.** Единая модель (25,3 млн параметров вместо 75,8 млн, один проход вместо трёх) обучается на одном потребительском GPU и не уступает трём моделям по среднему AUC, но общие параметры перераспределяют точность между задачами, а не увеличивают её. Перед клиническим применением необходима внешняя валидация. Код: https://github.com/Amanekkkk/MRNet_multihead.

Ключевые слова: МРТ колена, многозадачное обучение, ResNet50, классификация патологий, AUC, MRNet.

Introduction. Knee injuries are among the most common musculoskeletal complaints in orthopaedic and sports-medicine practice, and magnetic resonance imaging (MRI) is the reference standard for their non-invasive evaluation. A knee MRI examination is read across three orthogonal planes — axial, coronal and sagittal — each contributing complementary information about ligamentous, meniscal and osseous structures. Manual interpretation is time-consuming, requires subspecialty expertise and shows inter-observer variability, particularly for subtle anterior cruciate ligament (ACL) and meniscus pathology. This motivates automated tools that could triage studies, flag likely abnormalities or support less experienced readers in resource-limited settings.

Deep learning on volumetric MRI differs from standard 2D classification: examinations contain variable numbers of slices across several planes, and pathological signal is often confined to a few slices of an otherwise normal volume. Conditions also co-occur — for example, a meniscus tear alongside a general abnormality finding — which motivates a multi-task formulation that predicts several pathologies in one forward pass instead of deploying independent single-purpose models. A recent systematic review of 54 knee MRI deep-learning studies found that most models address a single pathology, most often ACL or meniscal tears, and that 82% of the studies reporting validation relied on internal validation only (Mead et al., 2025).

The MRNet dataset (Bien et al., 2018) comprises 1,370 knee MRI examinations from Stanford University Medical Center (1,130 training and 120 validation examinations are public), each labelled for general abnormality, ACL tear and meniscus tear. The original work and much of the subsequent literature combine separate single-task, single-view models through a logistic regression ensemble. A single multi-label model processing all three planes has been evaluated on MRNet, but it was trained from scratch and performed clearly below per-task ensembles (Azcona et al., 2020). Here we pursue a unified multi-task, multi-view architecture that shares one ImageNet-pretrained backbone across all three planes and all three tasks. Our hypothesis is that anatomically related pathologies share enough low- and mid-level visual structure for a shared representation to reduce the parameter count to about one third of that of three single-task models of the same architecture (25.3 M versus 75.8 M) while achieving comparable diagnostic performance. We test this against three single-task models trained under an identical protocol and evaluated once on a held-out test set.

Literature Review. Early automated MRI analysis relied on hand-crafted features such as texture descriptors and shape priors combined with classifiers such as support vector machines; these pipelines required extensive feature engineering and generalised poorly across scanners and protocols. Convolutional neural networks (CNNs) replaced them by learning representations directly from pixel data. Bien et al. (2018) introduced the MRNet dataset and model, in

which an ImageNet-pretrained AlexNet extracts features from each 2D slice, the features are max-pooled across slices, and separate per-plane, per-task networks are combined by logistic regression; this achieved AUCs of 0.937 (abnormality), 0.965 (ACL tear) and 0.847 (meniscus tear) on a held-out set of 120 examinations that now forms the hidden MRNet test set. This slice-wise, max-pooled design became the standard baseline for volumetric MRI with variable slice counts and directly informs the per-view encoder used here.

Subsequent work improved on this baseline in several directions. Tsai et al. (2020) proposed ELNet, a lightweight CNN trained from scratch with multi-slice normalisation and anti-aliased BlurPool down-sampling; using a single plane per task, it reached AUCs of 0.960 (ACL), 0.941 (abnormality) and 0.904 (meniscus) on the public MRNet validation set with fewer than 0.25 M parameters. Other work added attention within slices (Belton et al., 2021), across slices, channels and spatial positions (Wang et al., 2024), or across planes and sequences in a multi-task model for twelve knee abnormalities (Qiu et al., 2024). On MRNet, pyramidal feature details improved ACL and meniscus tear detection (Dunnhofer et al., 2021), and a comparative study identified transfer learning and tuned data augmentation as the crucial factors for per-task performance (Azcona et al., 2020). Fully volumetric 3D CNNs have graded cartilage, bone marrow, meniscal and ACL lesions (Astuto et al., 2021) and detected meniscal tears (Rizk et al., 2021; Tack et al., 2021), although 2D and 3D CNNs performed similarly for ACL injury staging (Namiri et al., 2020). Single-pathology CNNs also remain the norm in clinical validation: Tran et al. (2022) reported multi-continental external validation of an ACL tear detector trained on 19,765 examinations.

Multi-task learning (Caruana, 1997) trains a shared representation across related tasks and often generalises better than independent models, particularly when labelled data is scarce relative to model capacity, as it is for MRNet. In knee MRI, Tack et al. (2021) trained a single 3D CNN that detects meniscal tears in six anatomical sub-regions while regressing a meniscal bounding box; the auxiliary localisation task raised sub-region AUCs (e.g., from 0.87 to 0.94 for the medial anterior horn). Rizk et al. (2021) trained 3D CNNs for meniscal tear detection on more than 8,000 examinations; applied without retraining to the external MRNet cohort, tear detection reached an AUC of 0.83 (0.89 after fine-tuning), underscoring the effect of domain shift. On MRNet, Azcona et al. (2020) trained a single multi-plane, multi-label ResNet18 from scratch that reached a mean validation AUC of 0.83, against 0.93 for their best ensemble of ImageNet-pretrained per-task models. The common rationale is that related labels are driven by overlapping anatomical evidence, so a shared encoder can learn once what separate models would learn redundantly. Our three target pathologies share anatomy, frequently co-occur and are assessed from the same three planes.

Transfer learning from ImageNet (Russakovsky et al., 2015) is standard

practice in medical imaging, given the cost of expert annotation. ResNet (He et al., 2016) uses identity skip connections to ease the optimisation of very deep networks, and its variants are widely used as general-purpose feature extractors. ResNet50, with about 25 million parameters, balances capacity and computational cost and transfers well to medical imaging despite the domain shift to grayscale radiological images. Vision Transformers can match or exceed CNNs on some medical tasks but usually require larger training sets or extensive pretraining (Azad et al., 2024), which, given the modest size of MRNet, favours an ImageNet-pretrained ResNet50 as the shared per-view backbone of MVMT-MRNet.

Materials and Methods. The MRNet dataset (Bien et al., 2018) comprises 1,370 knee MRI examinations from Stanford University Medical Center, of which 1,130 training and 120 validation examinations are public; the remaining 120 form a hidden test set that was not used in this study. Every examination includes axial, coronal and sagittal series, stored as 8-bit arrays of shape (S, 256, 256), where the slice count S varies from 17 to 61. Each case carries three binary labels: (i) any abnormality, (ii) ACL tear and (iii) meniscus tear. Label statistics are summarised in Table 1.

Table 1 – Positive examinations per label in the MRNet public training split and in the training, validation and test subsets used in this study

Pathology	Public training split (N = 1,130)	Training subset (n = 960)	Validation subset (n = 170)	Test set: public validation (n = 120)
Abnormality	913 (80.8%)	776 (80.8%)	137 (80.6%)	95 (79.2%)
ACL tear	208 (18.4%)	177 (18.4%)	31 (18.2%)	54 (45.0%)
Meniscus tear	397 (35.1%)	337 (35.1%)	60 (35.3%)	52 (43.3%)

The three labels are treated as separate binary outputs because they are not mutually exclusive: one examination is frequently positive for more than one condition. A multi-label, multi-head formulation lets a single shared encoder be trained under one combined objective.

The 1,130 public training examinations are split into a training subset (960, 85%) and a validation subset (170, 15%) by stratification on the joint combination of the three labels (seed 42). The validation subset is used only for early stopping, checkpoint selection and the choice of decision thresholds. The 120 public MRNet validation examinations are never used for training or model selection; they serve as the held-out test set and are evaluated once with the selected checkpoint. Because this set is the benchmark of most follow-up work (e.g., Tsai et al., 2020; Azcona et al., 2020; Dunnhofer et al., 2021), our results are comparable with those studies, but not directly with Bien et al. (2018), whose AUCs were obtained on the hidden test set.

Figure 1 — Representative MRI slices from the MRNet training split. Columns: a normal knee (exam 0011), an ACL tear (exam 0046) and a meniscus tear (exam 0005); rows: axial, coronal and sagittal planes. Each panel shows the slice with the highest intensity variance within the central half of the volume, with its index.

Each volume is min-max scaled to [0, 1], replicated across three channels and normalised with the ImageNet channel statistics; the native 256 × 256 resolution is retained. During training, each volume is augmented with random rotation (±10°), translation (±5%), scaling (0.95–1.05), contrast change (0.9–1.1 about the volume mean) and brightness offset (±0.1, clamped to [0, 1]), sampled once per volume and applied identically to all its slices. A horizontal flip (probability 0.5), decided once per examination, is applied to the axial and coronal series, whose horizontal axis is left–right; sagittal series are not flipped, because this would swap anterior and posterior. Validation and test volumes are not augmented.

Our model, Multi-View Multi-Task MRNet (MVMT-MRNet), consists of one backbone shared by all three planes, three plane-specific projection layers, a shared fusion module and three task-specific classification heads (Figure 2). Given

a volume of shape (S×3×256×256), the ImageNet-pretrained ResNet50 (final fully connected layer removed, global average pooling retained) is applied to each slice, yielding 2048-dimensional features. A plane-specific linear layer with ReLU projects them to 256 dimensions, letting the model re-weight the shared features for each plane at about 0.5 M parameters per plane, and max-pooling over slices gives one 256-dimensional vector per view regardless of S.

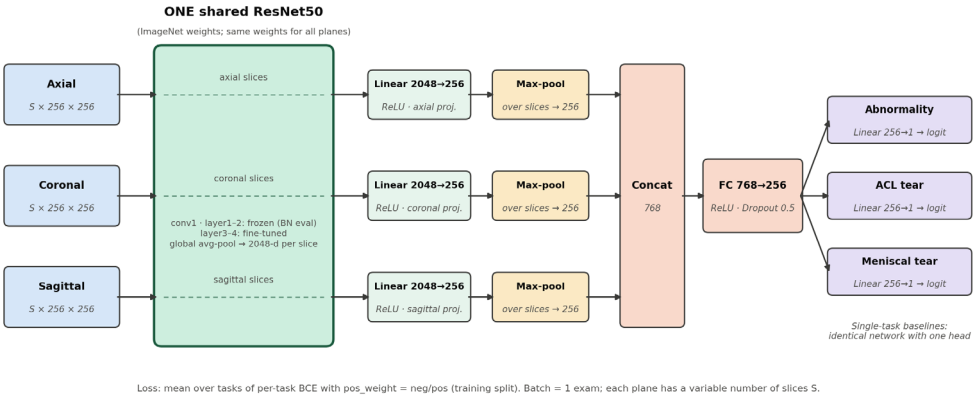

Figure 2 — MVMT-MRNet architecture. A shared ImageNet-pretrained ResNet50 (conv1, layer1 and layer2 frozen) extracts a 2048-dimensional vector from every slice; plane-specific projections (2048 → 256, ReLU) and max-pooling over slices give one 256-dimensional vector per plane, which are concatenated (768) and passed through a shared layer (768 → 256, ReLU, dropout 0.5) feeding three binary heads. The single-task baselines use the same network with one head.

The three view vectors are concatenated (768) and passed through a shared fully connected layer (768 → 256, ReLU, dropout 0.5), and three linear layers (256 → 1) produce one logit per pathology. As baselines, three single-task models (abnormality, ACL tear, meniscus tear) use the identical architecture and training protocol with one classification head each.

The backbone is initialised with ImageNet-1K weights. To reduce GPU memory and overfitting, the initial convolution, batch normalisation and the first two residual stages (layer1 and layer2) are frozen, with their batch normalisation layers kept in evaluation mode; only layer3, layer4 and the projection, fusion and classification layers are trained. The multi-task model has 25.28 M parameters (23.83 M trainable); the three single-task baselines together contain about 75.8 M.

Each task is an independent binary classification problem, and the total loss is the mean of the class-weighted binary cross-entropy losses of the three tasks:

$$L = (1/3)\, \Sigma_t \, BCE_w(\hat{y}_t, y_t), \quad t \in \{abn, acl, men\},$$

$$BCE_w(\hat{y}_t, y_t) = -[w_t \cdot y_t \cdot \log \sigma(\hat{y}_t) + (1 - y_t) \cdot \log(1 - \sigma(\hat{y}_t))]$$

where $\hat{y}_t$ is the predicted logit, $y_t \in \{0, 1\}$ the ground-truth label for task t, σ the logistic sigmoid and w_t the positive-class weight, set to the ratio of negative to positive examinations in the training subset (0.237 for abnormality, 4.424 for ACL tear and 1.849 for meniscus tear). The tasks are weighted equally.

The model is optimised with Adam (learning rate 8×10^{-5}, weight decay 1×10^{-5}) under a cosine annealing schedule over at most 100 epochs, down to a minimum of 8×10^{-7} (Loshchilov & Hutter, 2017). Because slice counts vary, one examination is processed per forward pass, and gradients are accumulated over eight examinations per optimiser step, giving an effective batch of eight and 120 steps per epoch. Padding volumes to a common slice count was rejected, because padded slices would enter the max-pooling over slices and could add spurious evidence; accumulation gives the same averaging while leaving every volume as acquired. The learning rate was scaled with the effective batch, from 1×10^{-5} at one examination per update to 8×10^{-5} at eight. Automatic mixed precision (FP16 autocast with a GradScaler) reduced peak allocated GPU memory from 4,609 MB to 2,597 MB (43.7%) and sped up training 1.76 times in a short benchmark. The framework uses PyTorch 2.9.1 with CUDA 12.8 on a single NVIDIA GeForce RTX 5060 Ti GPU (8 GB). The checkpoint with the highest validation mean AUC is kept, and training stops when this value has not improved for 20 epochs, but not before epoch 30.

Hyperparameters were selected by limited manual tuning, given the computational budget of a single consumer GPU. The weight decay and the single-examination learning rate of 1×10^{-5} follow the MRNet settings of Belton et al. (2021) and Dunnhofer et al. (2021); the augmentation ranges, dropout rate and early-stopping patience were fixed in advance. A learning rate of 1×10^{-4} collapsed: with the class-weighted loss, the model became a constant predictor within two epochs (training loss 0.766 against 0.765 for a constant output) and its validation mean AUC never exceeded 0.61. Diagnostic runs showed that at this rate the fraction of active projection ReLU units fell to 0–2% and the logits lost their spread, whereas at 1×10^{-5} about three quarters stayed active. Because a larger effective batch reduces gradient noise, the batch size and learning rate were chosen together over the four configurations in Table 4, on the validation subset alone; the test set played no part in any of these choices.

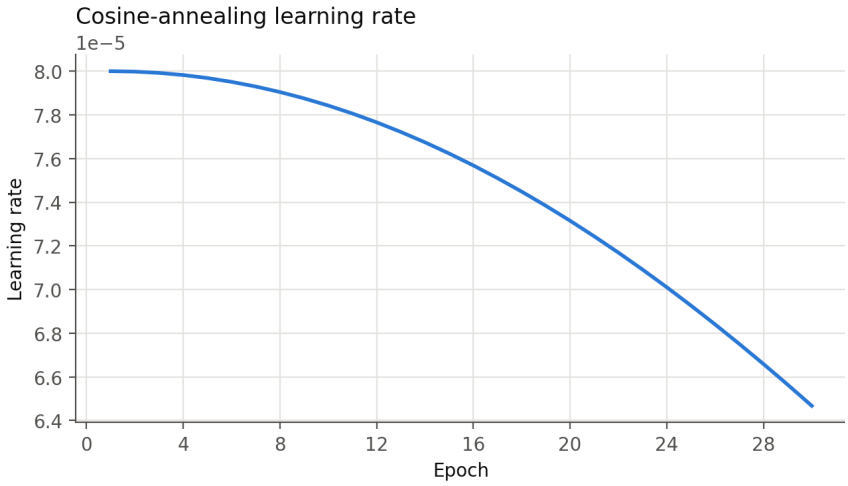

Figure 3 — Cosine annealing learning rate of the multi-task run, defined over 100 epochs from 8×10^{-5} to 8×10^{-7}; early stopping ended training at epoch 30, when the rate had fallen to 6.47×10^{-5}.

The selected checkpoint is evaluated once on the test set. For each task we report the AUC-ROC and the mean AUC over the three tasks, with 95% confidence intervals from a percentile bootstrap over examinations (2,000 resamples, seed 42). Sensitivity and specificity are reported at the threshold that maximises Youden's J statistic on the validation subset and at the default threshold of 0.5. The single-task baselines use exactly the same splits, augmentation, loss, optimiser, schedule and early-stopping rule. The comparison between the two designs is paired: the same resampled examinations are drawn for both models and the AUC difference is computed within each resample, so the intervals account for the correlation between predictions made on the same examinations.

Results. AUC is used as the primary metric because it is threshold-independent and robust to class imbalance, which matters given the 80.8% prevalence of the abnormality label.

The multi-task model trained for 30 epochs in 70 minutes on a single RTX 5060 Ti (139 s per epoch, peak allocated memory 2,836 MB). Validation mean AUC peaked at epoch 6 at 0.838 (0.834 for abnormality, 0.885 for ACL tear and 0.793 for meniscus tear) and never improved again, so early stopping ended the run at epoch 30; the epoch-6 checkpoint was carried forward to the test set. The curves show clear overfitting: training loss falls from 0.769 at epoch 1 to 0.500 at epoch 6 and 0.091 at epoch 30, while validation loss is lowest (0.65) at epoch 2, stands at 0.70 at the selected epoch, and peaks at 3.55 at epoch 26 before ending at 2.24 (Figure 4).

Validation mean AUC is far more stable than the loss, staying between 0.64 and 0.84 and ending at 0.730. Per task (Figure 5, left), ACL tear stays between 0.71 and 0.89 and ends at 0.885, whereas abnormality and meniscus tear peak in the first six

epochs and fall to 0.628 and 0.677 by epoch 30. Training mean AUC passes 0.92 by epoch 12 and reaches 0.980 (Figure 5, right), so the model memorises the 960 training examinations; early stopping on validation mean AUC keeps the selected checkpoint useful on unseen examinations.

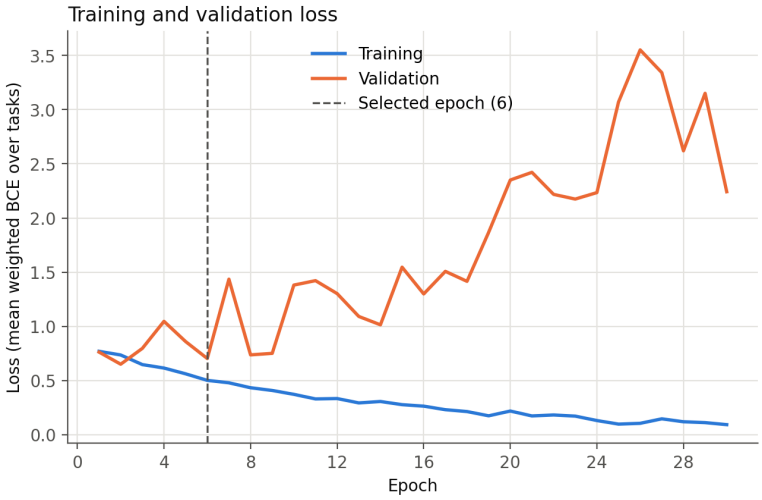

Figure 4 — Mean class-weighted binary cross-entropy loss of the multi-task model on the training and validation subsets over 30 epochs. The dashed line marks the selected epoch (6).

The epoch-6 multi-task checkpoint and the three single-task checkpoints were each evaluated once on the 120 held-out examinations (Table 2, Figure 6). The multi-task model reaches 0.844 for abnormality, 0.914 for ACL tear and 0.664 for meniscus tear (mean 0.807); the single-task models reach 0.825, 0.944 and 0.790 (mean 0.853). Every confidence interval excludes 0.5, but the intervals are wide, spanning up to 0.19 of AUC on a single task.

Table 2 — Held-out test-set AUC (120 examinations) of the multi-task and single-task models with 95% percentile bootstrap confidence intervals (2,000 exam-level resamples), and the paired difference between them

Task	Multi-task AUC [95% CI]	Single-task AUC [95% CI]	Difference, multi − single [95% CI]
Abnormality	0.844 [0.752, 0.922]	0.825 [0.724, 0.914]	+0.019 [−0.108, +0.150]
ACL tear	0.914 [0.857, 0.959]	0.944 [0.896, 0.978]	−0.030 [−0.095, +0.032]
Meniscus tear	0.664 [0.567, 0.757]	0.790 [0.703, 0.868]	−0.126 [−0.231, −0.020]
Mean	0.807 [0.749, 0.860]	0.853 [0.802, 0.897]	−0.046 [−0.115, +0.015]

On the mean, the two designs are statistically indistinguishable: the paired difference is −0.046 (95% CI −0.115 to +0.015). Per task, sharing the encoder costs 0.126 of AUC on meniscus tear (−0.231 to −0.020), the only interval that

excludes zero; it is nominally worse on ACL tear by 0.030 (−0.095 to +0.032) and nominally better on abnormality by 0.019 (−0.108 to +0.150). On the same 120 examinations, ELNet reports 0.941, 0.960 and 0.904 for abnormality, ACL tear and meniscus tear (Tsai et al., 2020), MRPyrNet reports 0.976 for ACL tear and 0.889 for meniscus tear (Dunnhofer et al., 2021), and the only other single multi-label model reports a mean of 0.828 (Azcona et al., 2020). Our single-task ACL tear result of 0.944 is close to these, and the multi-task 0.914 is not far behind; abnormality and especially meniscus tear detection remain clearly below them. The AUCs of Bien et al. (2018) were measured on the hidden test set and are not directly comparable.

Table 3 reports the sensitivity and specificity of the multi-task model at the validation-derived Youden threshold and at 0.5. The validation thresholds are 0.288 for abnormality, 0.565 for ACL tear and 0.529 for meniscus tear. At these thresholds the ACL head finds 46 of the 54 ACL tears at a specificity of 0.848, the abnormality head finds 90 of the 95 abnormal examinations at a specificity of only 0.400, and meniscus tear detection reaches a sensitivity of 0.827 at a specificity of 0.426.

Table 3 – Sensitivity and specificity of the multi-task model on the held-out test set, at the threshold that maximises Youden's J statistic on the validation subset and at the default threshold of 0.5

Task	Validation threshold	Sensitivity	Specificity	Sensitivity at 0.5	Specificity at 0.5
Abnormality	0.288	0.947	0.400	0.884	0.560
ACL tear	0.565	0.852	0.848	0.907	0.818
Meniscus tear	0.529	0.827	0.426	0.827	0.382

The practical case for sharing is size and cost. The multi-task model holds 25,279,299 parameters (23,834,371 trainable); each single-task model holds 25,278,785, so the three together hold 75,836,355, and classifying one examination requires three forward passes instead of one. Training took 70 minutes for the multi-task model against 69, 129 and 69 minutes for the abnormality, ACL tear and meniscus tear models, 267 minutes in total. The shared model therefore delivers comparable mean accuracy at one third of the parameters and inference cost and about a quarter of the training time, while giving up 0.126 of AUC on meniscus tear.

Figure 5 — Left: validation AUC per task and their mean for the multi-task run. Right: training mean AUC (with augmentation and dropout active) against validation mean AUC. The dashed line marks the selected epoch (6).

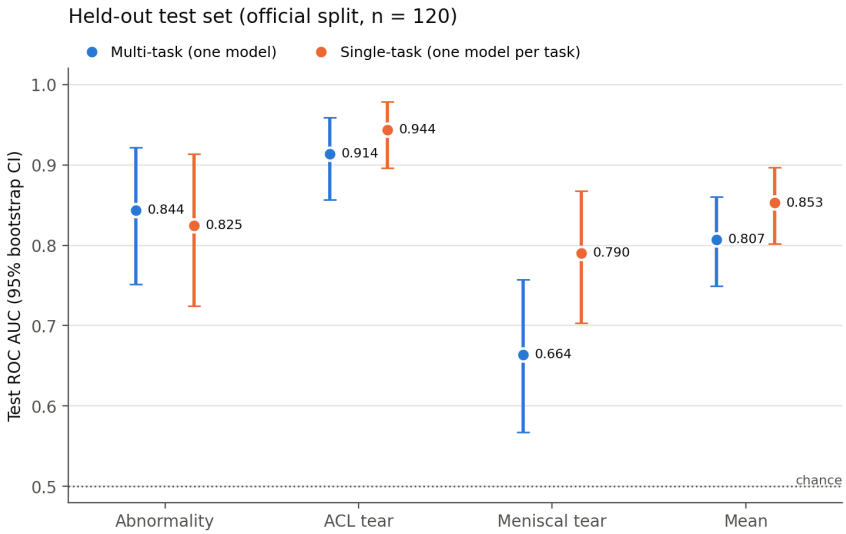

Figure 6 — Test-set AUC of the multi-task and single-task models on the 120 held-out examinations, with 95% percentile bootstrap confidence intervals (2,000 exam-level resamples).

Effect of the effective batch size and the learning rate. Because a batch of one examination gives noisy gradient estimates, we compared four configurations of the multi-task model that differ only in the number of examinations averaged per optimiser step and in the learning rate; everything else is identical. Table 4 gives the validation mean AUC on which the choice was made and, for completeness, the test results.

Table 4 – Effect of the effective batch size and the learning rate on the multi-task model. The protocol was chosen on the validation mean AUC; test AUCs (95% bootstrap confidence intervals) are reported for completeness only. The third row is the final protocol.

Exams per update	Learning rate	Best epoch / epochs run	Validation mean AUC	Test AUC (abn / ACL / men)	Test mean AUC [95% CI]
1 (previous protocol)	1×10^{-5}	15 / 35	0.768	0.775 / 0.914 / 0.645	0.778 [0.713, 0.836]
8	1×10^{-5}	5 / 30	0.751	0.700 / 0.754 / 0.600	0.685 [0.618, 0.745]
8 (final protocol)	8×10^{-5}	6 / 30	0.838	0.844 / 0.914 / 0.664	0.807 [0.749, 0.860]
1 (control)	8×10^{-5}	4 / 30	0.628	0.702 / 0.435 / 0.616	0.584 [0.509, 0.659]

A larger effective batch helps only when the learning rate is scaled with it. Averaging over eight examinations at 1×10^{-5} makes matters worse (validation mean AUC 0.751 against 0.768, test 0.685 against 0.778), because each epoch now contains one eighth as many optimiser steps and the model is undertrained. Raising the rate to 8×10^{-5} recovers those steps and improves on both runs, to 0.838 on validation and 0.807 on test. The same rate at one examination per update diverges: validation mean AUC falls to 0.628 and test ACL tear AUC collapses to 0.435, below chance — the same failure described in Methods for 1×10^{-4}. At a batch of one the class-weighted objective tolerates 1×10^{-5} but not 8×10^{-5}, whereas averaging over eight examinations makes 8×10^{-5} the best of the four. The choice was made on the validation column of Table 4 alone.

Discussion. One shared model carries three knee MRI tasks at an average accuracy that cannot be told apart from three separate models, but not at the same accuracy on every task. The mean test AUCs are 0.807 and 0.853 (paired difference −0.046, 95% CI −0.115 to +0.015), while the shared model holds 25.3 M parameters against 75.8 M and needs one forward pass instead of three. The cost appears per task: meniscus tear detection loses 0.126 of AUC (−0.231 to −0.020), ACL tear detection is nominally worse by 0.030 and abnormality detection nominally better by 0.019. Parameter sharing redistributes accuracy across the tasks rather than adding it.

The direction of these shifts follows from the labels. General abnormality is the broadest, positive for any deviation from a normal knee, so most of the evidence the other two heads need is evidence for it as well; a shared encoder has little to lose on this task, the classic condition under which multi-task learning helps (Caruana, 1997). A meniscus tear is the opposite case: often a subtle intra-substance signal change confined to a few slices, with the least stereotyped appearance of the three. A representation shaped largely by the broad abnormality label and the more conspicuous ACL findings is a worse basis for it than one trained on the meniscus label alone. ACL tears lie in between: localised findings with a stereotyped appearance — fibre discontinuity, raised T2 signal, an altered ligament slope — that both designs detect well. Both meniscus results remain below the 0.904 of ELNet on the same examinations (Tsai et al., 2020), so

representing subtle meniscal change is a limitation of this architecture as a whole, not only of sharing it.

Overfitting has been reduced rather than eliminated. Volume-level augmentation, applied consistently to every slice of an examination, is used for all training volumes; a systematic review of more than 300 medical imaging studies found such geometric and intensity transformations effective across organs, modalities, tasks and dataset sizes (Garcea et al., 2023). Together with early stopping, this makes the selected checkpoint useful on unseen data (validation mean AUC 0.838, test 0.807). Still, training mean AUC is 0.859 at the selected epoch and 0.980 by epoch 30 while validation loss rises from epoch 3, and the larger effective batch has if anything sharpened this pattern. Stronger regularisation and freezing the backbone through layer3 remain untested.

The batching study (Table 4) shows how much of the earlier gap came from optimisation rather than architecture. Changing only the effective batch size and learning rate moved the multi-task test mean AUC from 0.778 to 0.807 and single-task meniscus tear detection from 0.644 to 0.790. Gradient accumulation thus answers the objection to a batch of one examination without the padding that max-pooling over slices makes unattractive, and the batch size and learning rate cannot be tuned independently here. What better optimisation does not remove is the meniscus deficit under sharing, which is now larger and is the one per-task difference that the confidence intervals resolve.

Class imbalance runs in opposite directions across tasks: the abnormality label is positive for 80.8% of the training subset and the ACL label for only 18.4%. The per-task positive weights (0.237, 4.424 and 1.849) show their effect mainly in the operating points: with one examination per update the ACL head reached a sensitivity of 0.870 only at a validation-chosen threshold of 0.027, whereas under the final protocol the thresholds are 0.288, 0.565 and 0.529. The abnormality head still buys a sensitivity of 0.947 at a specificity of only 0.400, so any deployment would have to choose its thresholds explicitly. The weighting also interacts with the learning rate, driving the network to a constant predictor at 1×10^{-4} and ACL tear detection below chance at 8×10^{-5} with one examination per update. Focal loss (Lin et al., 2017) and post-hoc calibration are natural alternatives to test.

Several architectural alternatives merit investigation. Attention-weighted slice aggregation, as explored for ACL tear detection on MRNet (Wang et al., 2024), could down-weight uninformative slices instead of treating one maximally activating slice as representative of the whole volume, a simplification that may be costly for diffuse or multi-focal pathology. Task-specific rather than fully shared fusion layers could retain a shared low-level representation while allowing task specialisation, potentially recovering the meniscus tear accuracy lost under full sharing. Transformer-based multi-view fusion is a further option once sufficient pretraining is available (Azad et al., 2024).

This study has several limitations. First, no external cohort was used: all data come from a single institution, so unlike the external validations of Tran et al.

(2022) and Rizk et al. (2021), we have no evidence of transfer to other scanners and protocols. Second, the official MRNet test set is withheld and was not evaluated, so our results are not directly comparable with Bien et al. (2018). Third, each configuration was trained once from a single seed; the paired bootstrap covers the sampling of examinations but not run-to-run variance, so the per-task differences and the ordering in Table 4 are indicative rather than established. Fourth, the protocol was selected over only four configurations on 170 validation examinations, which selects noisily. Fifth, the 120-examination test set gives wide intervals, about ±0.06 on the mean AUC and ±0.10 on a single task. Sixth, overfitting has been contained but not solved. Seventh, meniscus tear detection (0.664 shared, 0.790 single-task) is below published work on the same examinations and would have to improve before any clinical use. Finally, multi-centre external validation with reader studies, as performed for a multi-abnormality knee MRI model (Qiu et al., 2024), and prospective evaluation would be necessary before clinical deployment.

Conclusion. We presented MVMT-MRNet, a multi-task, multi-view framework that classifies three knee MRI pathologies with one ResNet50 backbone shared across the axial, coronal and sagittal planes and across all tasks, trained with gradients averaged over eight examinations per update. On the 120 held-out examinations of the public MRNet validation set it reaches a mean AUC of 0.807 (95% CI 0.749–0.860), with 0.844 for abnormality, 0.914 for ACL tear and 0.664 for meniscus tear. Three single-task models of the same architecture reach 0.853 (0.802–0.897), and the paired difference of −0.046 (−0.115 to +0.015) includes zero. The shared model is thus statistically indistinguishable on average accuracy while holding 25.3 M parameters instead of 75.8 M and needing one forward pass instead of three, but it is significantly worse on meniscus tear detection (−0.126, −0.231 to −0.020): parameter sharing redistributes accuracy rather than adding it. A larger effective batch helps only when the learning rate is scaled with it, and much of the gap observed with one examination per update was due to optimisation rather than architecture. Abnormality and especially meniscus tear detection remain below published results, and overfitting on 960 training examinations remains the binding constraint. The code is publicly available to support reproducibility (https://github.com/Amanekkkk/MRNet_multihead).

More broadly, on small, high-dimensional medical imaging datasets, cross-task sharing saves parameters but is not free on every task, and optimisation deserves at least as much attention as architecture: changing only the effective batch size and learning rate moved the results by more than sharing the encoder did.

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