KNEE INJURY DETECTION USING MRI WITH EFFICIENTLY LAYERED NETWORK (ELNET)

Chen-Han Tsai, Nahum Kiryati, Eli Konen, Iris Eshed, Arnaldo Mayer

TEL AVIV UNIVERSITY

Sheba Medical Center
Tel HaShomer
ISRAEL'S CITY OF HEALTH

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PROBLEM MOTIVATION

CONVENTIONAL KNEE EXAMS

MRI Acquisition

Queue	Patient ID	Age	Pathology	Exam Date
1	13059684	49	ACL	June-3-2019 - 10:14:05
2	23615409	25	Meniscus	June-3-2019 - 10:48:21
3	32156089	36	Meniscus	June-3-2019 - 11:23:31
4	21410238	42	Osteoarthritis	June-3-2019 - 11:44:52
5	14796243	46	Effusion	June-3-2019 - 12:21:13
6	61325967	52	ACL	June-3-2019 - 12:46:01
7	32651489	61	ACL	June-4-2019 - 10:12:07
8	62354782	23	PCL	June-4-2019 - 10:47:09
9	25614503	35	Fracture	June-4-2019 - 11:20:21

Exam added to Queue

Sorted by Exam Date

Doctor's Analysis

Final Assessment

- MSK radiologists face a rising work demand each day
- Triage improves efficiency by prioritization
- Severe cases prioritized first

PROBLEM MOTIVATION

TRIAGED KNEE EXAMINATIONS

MRI Acquisition

Queue	Patient ID	Age	Pathology	Exam Date
	25614503	35	Fracture	June-4-2019 - 11:20:21
	61325967	52	ACL	June-3-2019 - 12:46:01
	14796243	46	Effusion	June-3-2019 - 12:21:13
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Sorted by
Level of Severity

Doctor’s Analysis

Final Assessment

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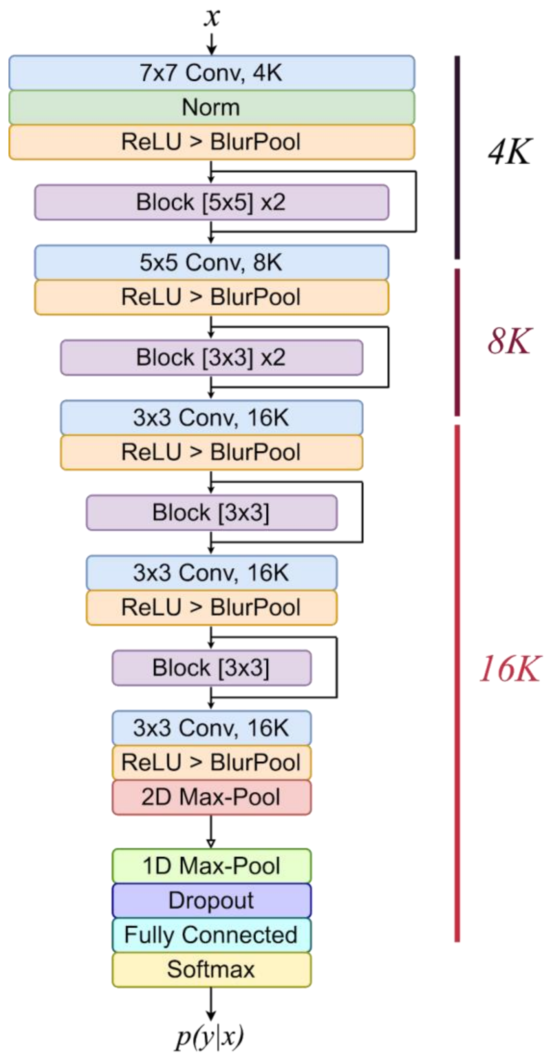
ELNET ARCHITECTURE



Output Size	Layer Operation	Trainable Parameters
$s \times 4K \times 128 \times 128$	7×7 Conv, $4K$	$196K$
	Normalization	$4K$
$s \times 4K \times 62 \times 62$	ReLU $\rightarrow$ BlurPool	
	Block $[5 \times 5] \times 2$	$800K^2 + 16K$
$s \times 8K \times 62 \times 62$	5×5 Conv, $8K$	$800K^2$
$s \times 8K \times 29 \times 29$	ReLU $\rightarrow$ BlurPool	
	Block $[3 \times 3] \times 2$	$1152K^2 + 32K$
$s \times 16K \times 29 \times 29$	3×3 Conv, $16K$	$1152K^2$
$s \times 16K \times 13 \times 13$	ReLU $\rightarrow$ BlurPool	
	Block $[3 \times 3]$	$2304K^2 + 32K$
	3×3 Conv, $16K$	$2304K^2$
$s \times 16K \times 5 \times 5$	ReLU $\rightarrow$ BlurPool	
	Block $[3 \times 3]$	$2304K^2 + 32K$
	3×3 Conv, $16K$	$2304K^2$
$s \times 16K$	ReLU $\rightarrow$ BlurPool $\rightarrow$ 2D Max-Pool	
$16K$	1D Max-Pool $\rightarrow$ Dropout	
2	Fully Connected $\rightarrow$ Softmax	$32K + 2$
	Total Trainable Parameters	$13120K^2 + 348K + 2$

Fig-1: Illustration and configuration of ELNet.

ELNET CORE COMPONENTS

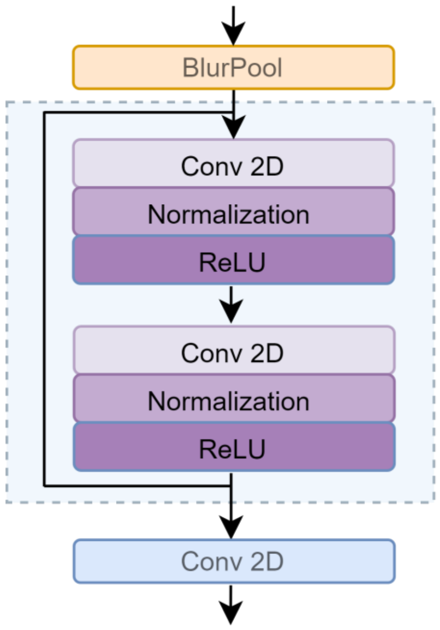
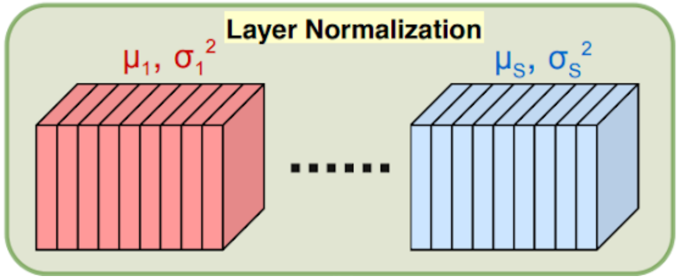
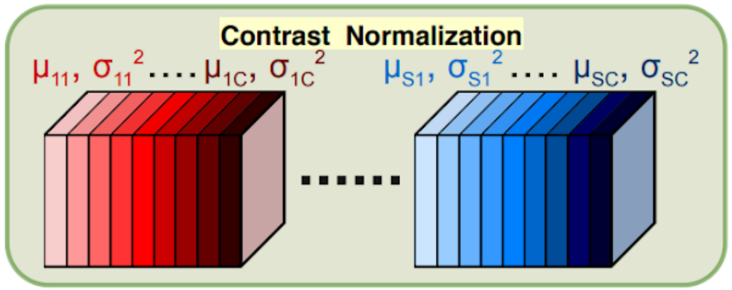


Fig-2: Block with 2 repeats



$$\hat{x}_n = \frac{x_n - \mu_n}{\sqrt{\sigma_n^2 + \epsilon}} \rightarrow y_n = \gamma \hat{x}_n + \beta \qquad \forall n : 1 \rightarrow N$$



$$\hat{x}_{nc} = \frac{x_{nc} - \mu_{nc}}{\sqrt{\sigma_{nc}^2 + \epsilon}} \rightarrow y_{nc} = \gamma \hat{x}_{nc} + \beta \qquad \forall n : 1 \rightarrow N, c : 1 \rightarrow C$$

Fig-3: Multi-slice Normalization for 3D Inputs

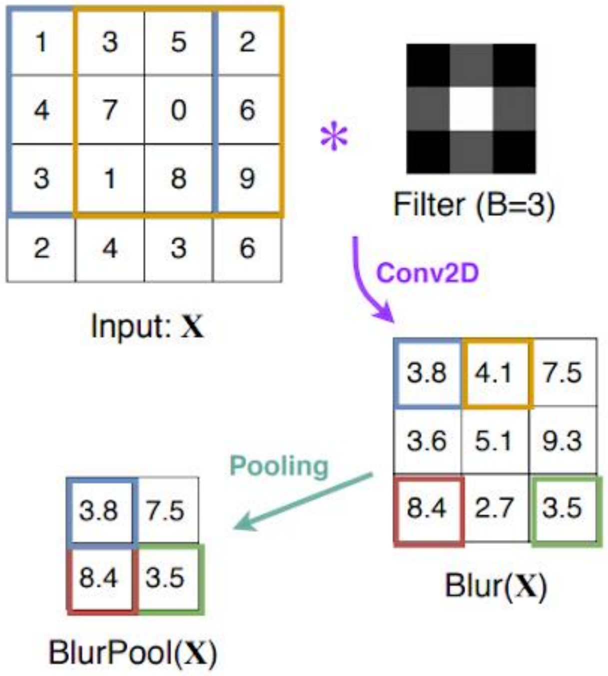


Fig-4: BlurPool Down-sampling

EVALUATION DATASETS

- **MRNet Dataset**[1]
  - 1370 knee MRI exams*
  - Labels : ACL tear / Meniscus tear / Abnormalities
  - Axial, coronal, and sagittal scans provided
- **KneeMRI Dataset**[2]
  - 917 knee MRI exams**
  - Labels: ACL Injured
  - Sagittal scan provided

Axial Plane

Coronal Plane

Sagittal Plane

[1] *Bien et al, Deep-learning-assisted diagnosis for knee magnetic resonance imaging: Development and retrospective validation of MRNet, PLOS Medicine (2018)*

[2] *Štajduhar et al, Semi-automated detection of anterior cruciate ligament injury from MRI, Computer Methods and Programs in Biomedicine (2017)*

ELNET SETUP

Detection Objective	Multi-Slice Norm	Image Modality	K	Number of Parameters
Meniscus Tear	Contrast Norm	Coronal	4	~ 0.2 M (850 kB)
ACL Tear	Layer Norm	Axial	4	-
Abnormalities	Layer Norm	Axial	4	-
ACL Tear (KneeMRI)	Contrast Norm	Sagittal	2	~ 0.05 M (438 kB)

- ELNet is trained from scratch
- Previous SOTA MRNet ~183M parameters for each objective

MRNET EVALUATION

Architecture	Pathology	Accuracy	Sensitivity	Specificity	ROC-AUC	MCC
MRNet	Meniscus Tear	0.735	0.827	0.662	0.826	0.489
	ACL Tear	0.9	0.907	0.894	0.956	0.769
	Abnormality	0.883	0.947	0.64	0.936	0.628
ELNet	Meniscus Tear	0.88	0.86	0.89	**0.904**	**0.745**
	ACL Tear	0.904	0.923	0.891	**0.960**	**0.815**
	Abnormality	0.917	0.968	0.72	**0.941**	**0.736**

Fig-5: Evaluation of ELNet and MRNet performance on the MRNet Dataset

KNEEMRI EVALUATION

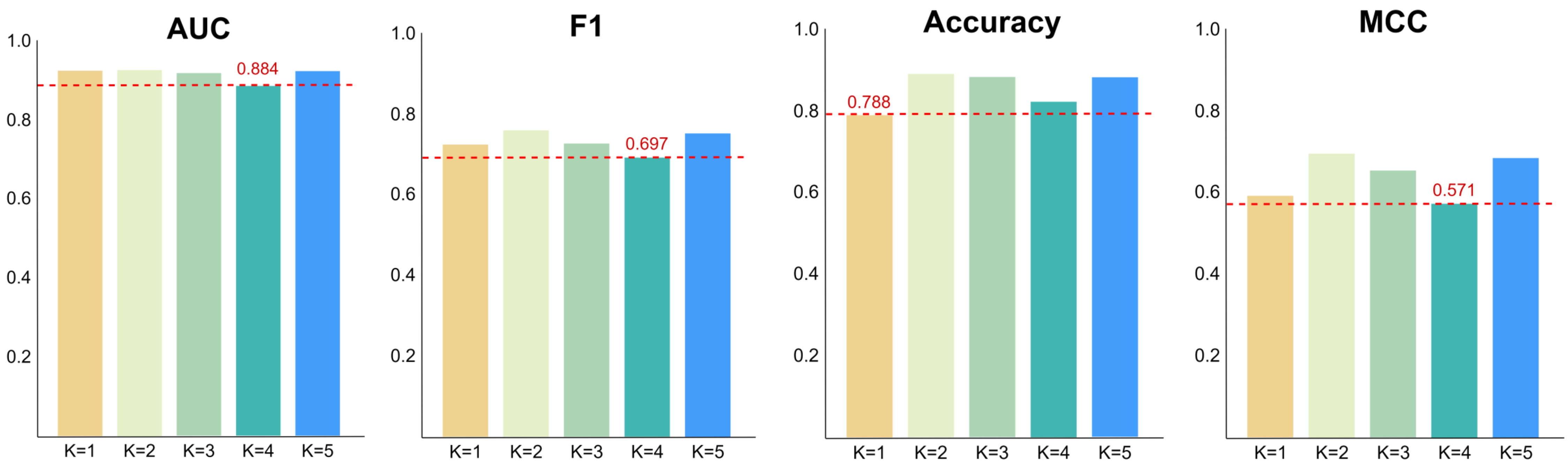


Fig-6: Comparison of ELNet performance across all 5 folds on the KneeMRI dataset

KNEEMRI EVALUATION

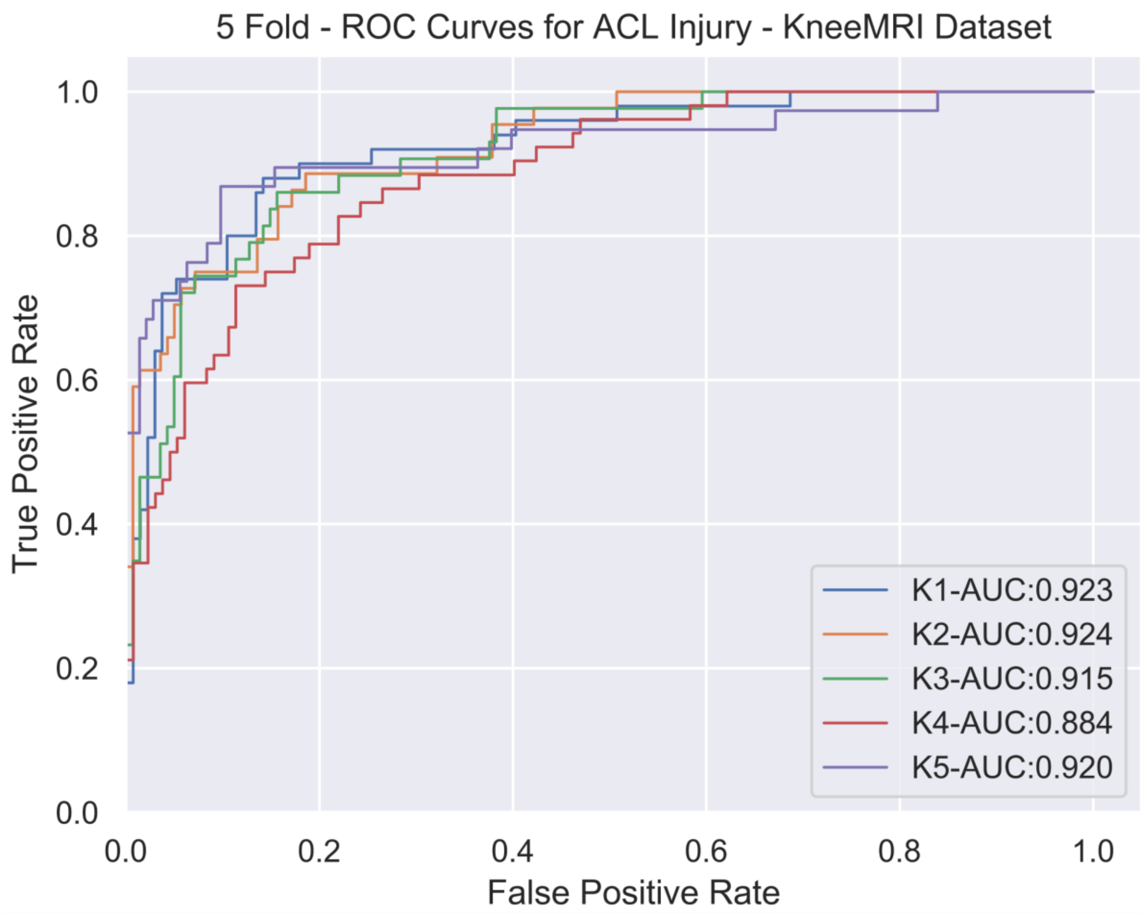


Fig-7: ROC's of ELNet of KneeMRI Dataset across 5 folds

MODEL INTERPRETATION

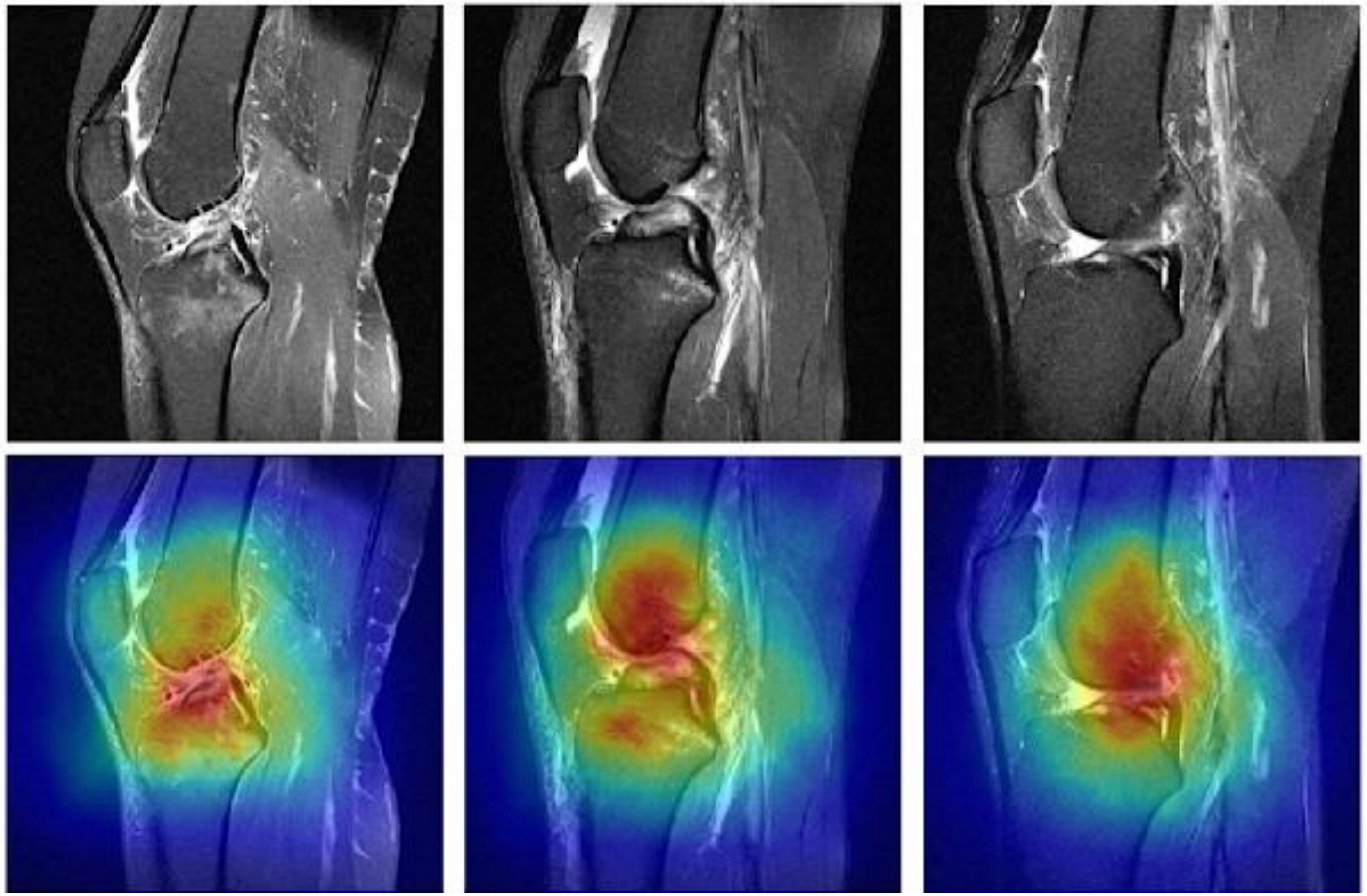


Fig-8: Full-Grad visualization highlighting the tear locations in the knee

SUMMARY

- ELNet features
  - Lightweight
  - Adequate performance
  - Easily trained from scratch

- May be applied to other pathologies involving 3D images (MRI, CT, etc.)