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Exploring Classification of Histological Disease Biomarkers from Renal Biopsy Images

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MOTIVATION:

➢ Kidney diseases affect millions of people worldwide. These can be prevented from reaching end stage by early detection through biopsy.
➢ Dearth of specialists makes this even more difficult

INTUITION:

➢ Counting number of abnormal glomerulus in a biopsy tissue is first thing checked for a diseased kidney
➢ Percentage of scarring in tissue (Fibrosis) gives idea about the damage to kidney tissue
➢ Machine learning and Deep learning techniques have proven to solve similar problems

Renal Glomeruli Fibrosis Histopathology database

Renal Glomeruli Dataset

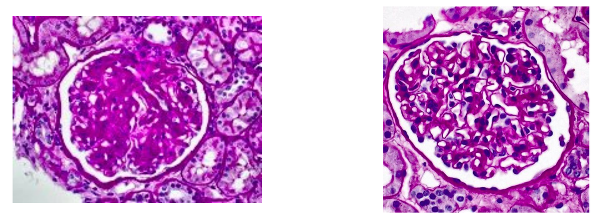
Label	Count
Abnormal	619
Normal	316
Total	935

Table 1: Image label distribution in RGD

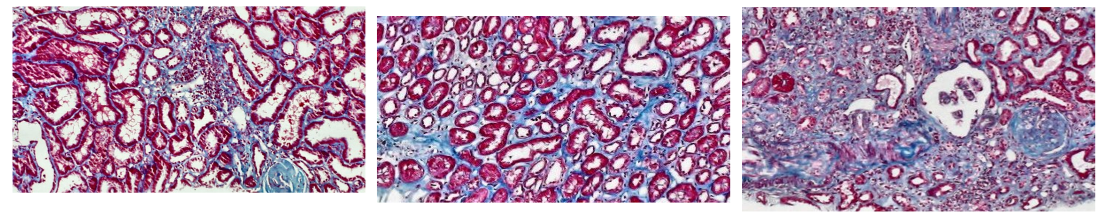
Renal Fibrosis Dataset

Label	Count
Mild	356
Moderate	198
Severe	373
Total	927

Table 2: Image label distribution in RFD



- Abnormal: diseased glomerulus
- Normal: healthy glomerulus

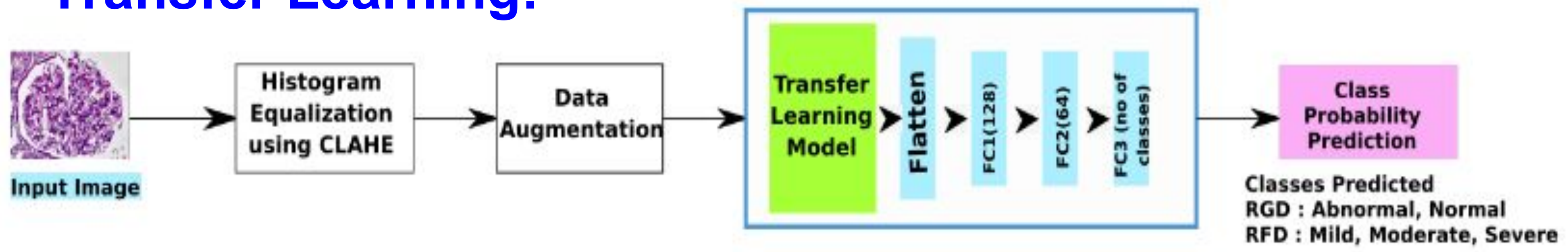


- Mild: 5−25% scarring
- Moderate: 26 − 50% scarring
- Severe: more than 50% scarring

**approximate values as per medical evaluation*

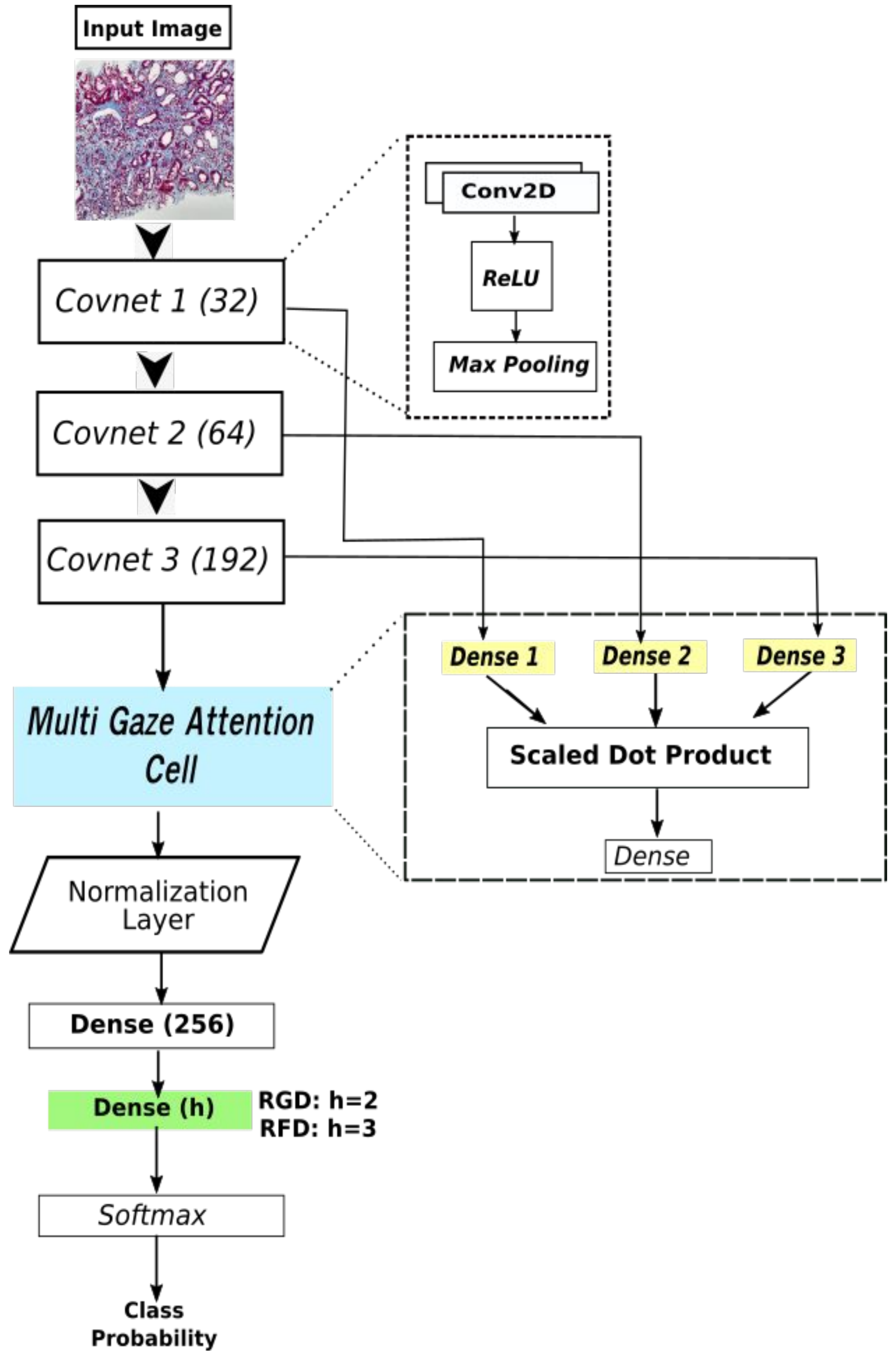
FRAMEWORKS:

Transfer Learning:



Supervised Classification with DNN Feature Extraction:

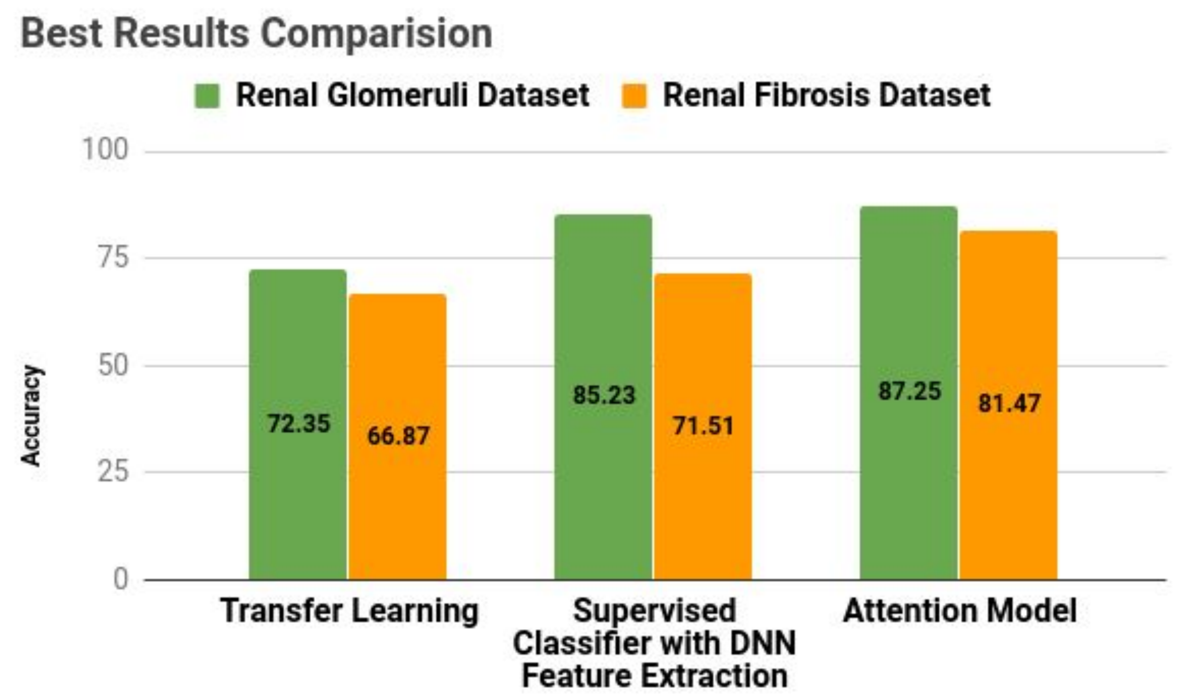
Multi-Gaze Attention Network (MGANet):



➢ MGANet uses **multi-headed self-attention**
➢ **3 attention maps** are generated over the WSI through residual skip connections from the initial ConvNet layers in parallel.
➢ Each of the three attention maps are appended and their **scaled dot product** is computed.
➢ The model jointly attends to information from different representation sub-spaces at different positions.
➢ A triplet of the **three distinct attention maps - a1, a2 and a3,** is then passed through the scaled dot product function where the scaled product of vectors a1 and a3 is passed to get the Softmax over vector a2, as shown below.
➢ a1, a2 and a3 are permuted for best results.

$$Attention(\alpha 1, \alpha 2, \alpha 3) = \frac{Softmax(\alpha 1, \alpha 2) * \alpha 3}{\sqrt{max(\alpha 1, \alpha 3)}}$$

RESULTS:



CONCLUSIONS:

➢ Feature extraction with supervised learning gives better results than simple transfer learning.
➢ MGANet outperforms both transfer learning as well as feature extraction based supervised classification techniques.
➢ The relative order of attention maps used for calculating the scaled dot product attention did not have a convincing influence on the performance metrics