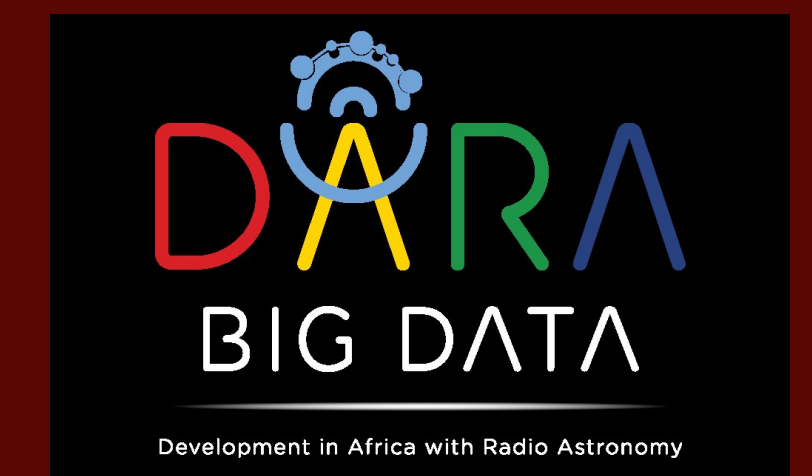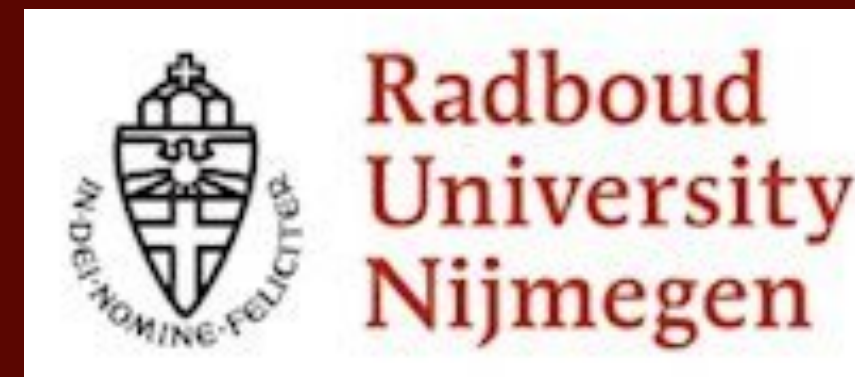# MeerCRAB: Classification of Optical Transients at the MeerLICHT Telescope using Deep Learning
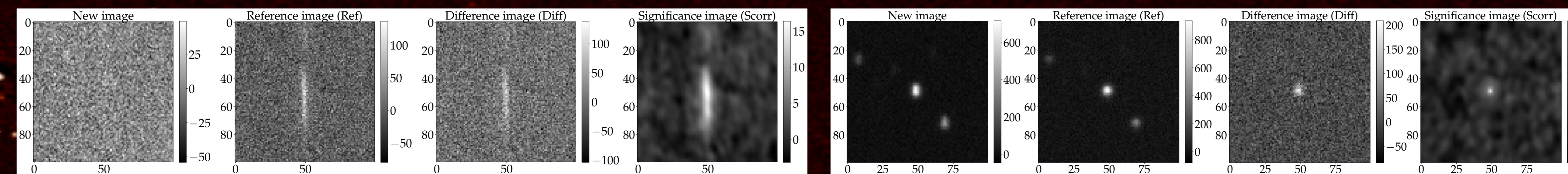
Zafiirah Hosenie[1], Paul Groot[2,3], Robert Lyon[4], Benjamin Stappers[1] & The MeerLICHT Team[3]

NEURAL INFORMATION PROCESSING SYSTEMS [1]

Radboud University Nijmegen [2]

MeerLICHT South Africa [3]

Edge Hill University [4]

DARA BIG DATA — Development in Africa with Radio Astronomy
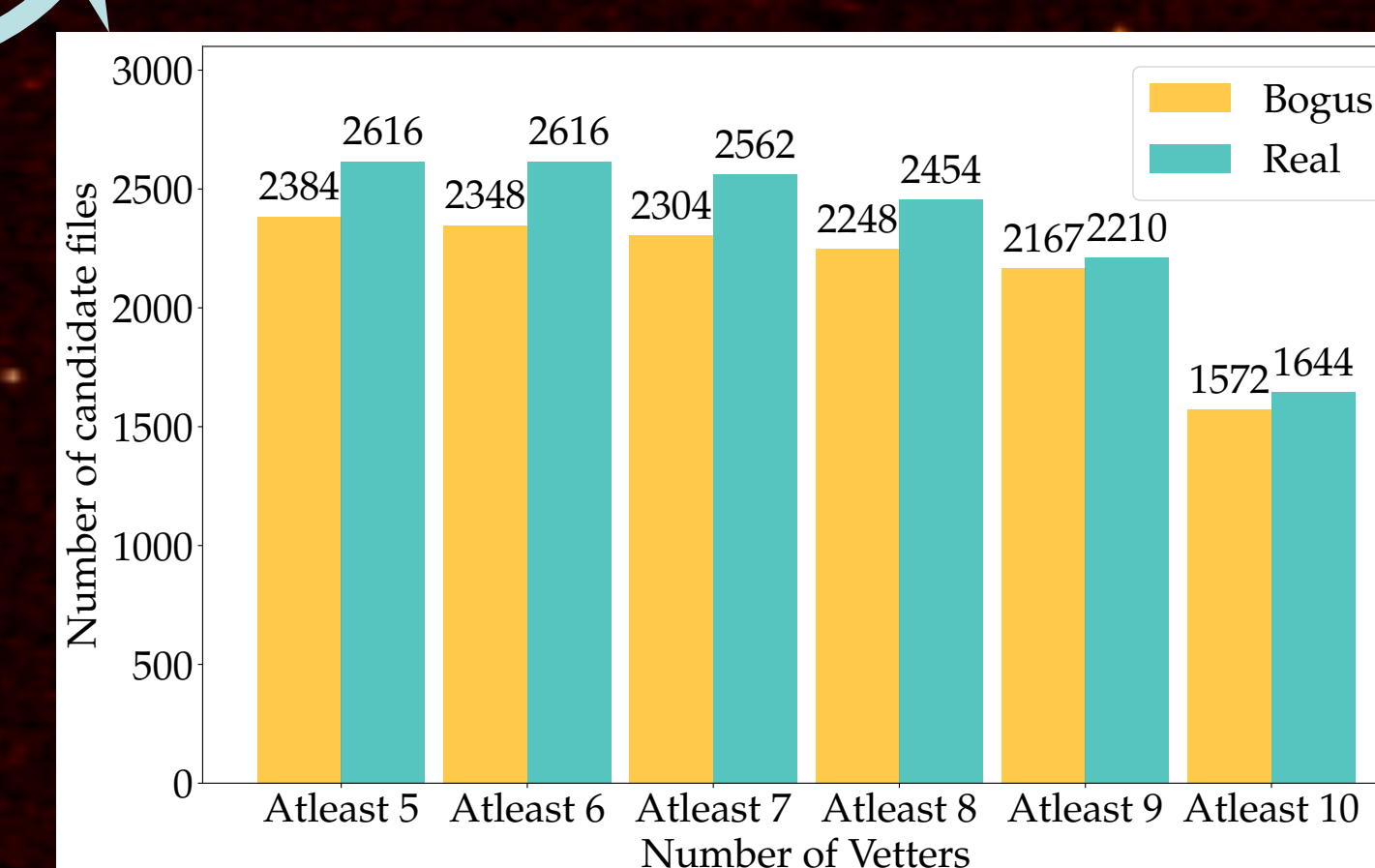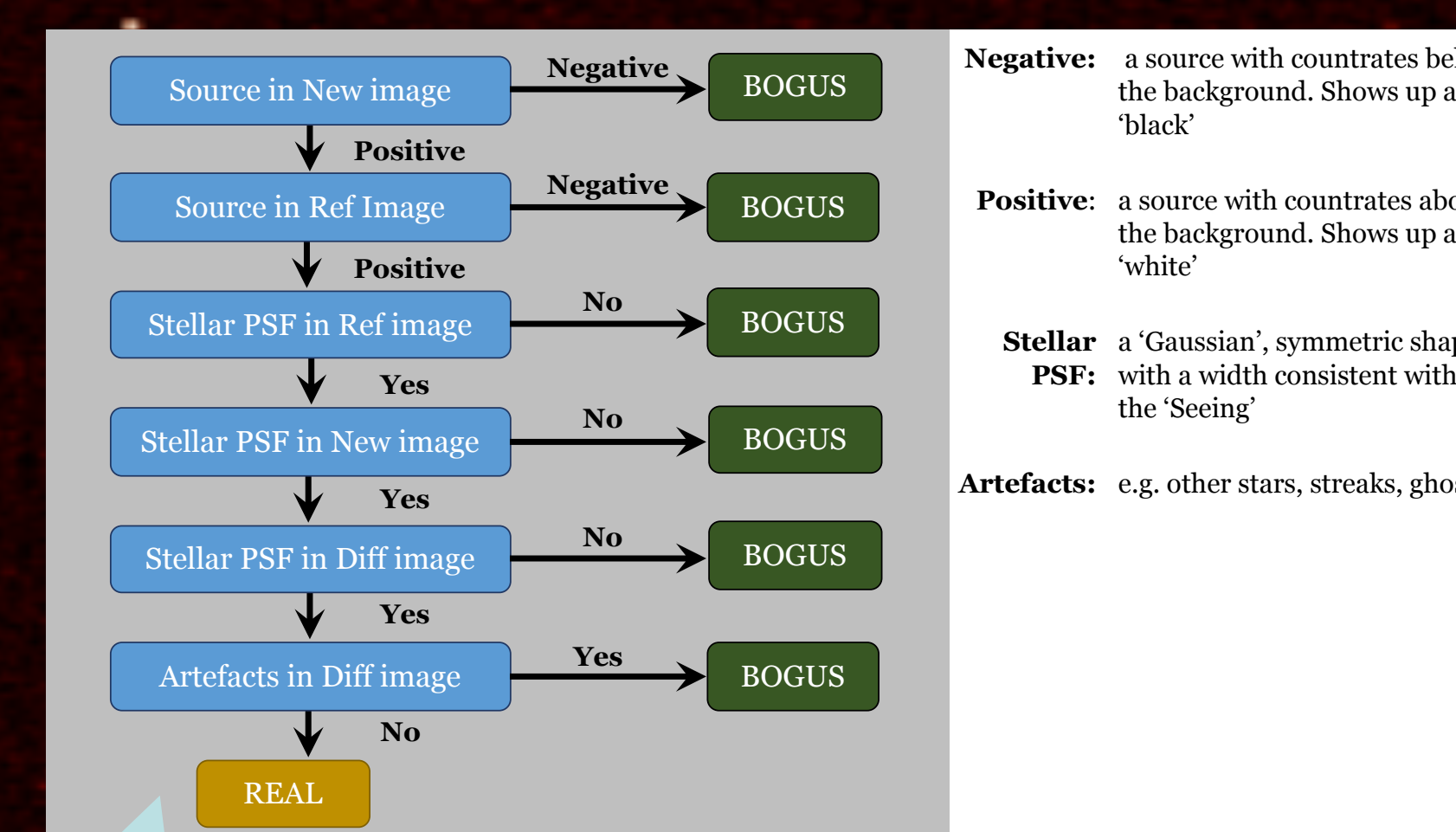
1. Input Data

- MeerLICHT is an optical wide-field telescope that is operated robotically.

- There are four distinct forms of image inputs to MeerCRAB – the new (N) image, the reference (R) image, the difference (D), & the significance (S) image.

New image | Reference image (Ref) | Difference image (Diff) | Significance image (Scorr)

Negative: a source with countrates below the background. Shows up as 'black'

Positive: a source with countrates above the background. Shows up as 'white'

Stellar PSF: a 'Gaussian', symmetric shape with a width consistent with the 'Seeing'

Artefacts: e.g. other stars, streaks, ghosts

Source in New image → Negative → BOGUS
↓ Positive
Source in Ref Image → Negative → BOGUS
↓ Positive
Stellar PSF in Ref image → No → BOGUS
↓ Yes
Stellar PSF in New image → No → BOGUS
↓ Yes
Stellar PSF in Diff image → No → BOGUS
↓ Yes
Artefacts in Diff image → Yes → BOGUS
↓ No
REAL

2. Constructing Training Data

- We construct a large representative training dataset (5000 candidates) for the Real-Bogus challenge.

- Manually vetting a selection of transients, using a web-interface, known as MeerVETTING.

- Each candidate is vetted by 10 volunteers, who are shown three images (N, R, D) during vetting.

Number of candidate files vs Number of Vetters:

	Bogus	Real
Atleast 5	2384	2616
Atleast 6	2348	2616
Atleast 7	2304	2562
Atleast 8	2248	2454
Atleast 9	2167	2210
Atleast 10	1572	1644

Latent Class Model

3. Methods of Labelling

a. **Latent class model (LCM)** will try to detect the presence of latent classes (the candidates entities), generating patterns of association in the characteristics.

b. **Thresholding Method**
We assign a probability P (*Real*) and P (*Bogus*) to each vetted candidate as follows:

$$P(Real) = \frac{n(R)}{n(T)}; \; P(Bogus) = \frac{n(B)}{n(T)}$$

4. MeerCRAB Models:

- During training, the binary cross-entropy loss function, Adam optimizer with a low lr = 0.0002 & a batch-size of 64 were used.

- We then split our data into 50% training, 25% validation and 25% testing.

- As input to the MeerCRAB models, we cropped the images from centre to a size of (30 × 30).

5. Results & Analysis

Effects of noisy data labelling on performance: As the threshold increased from T8 to T10, the accuracy of the model increases from 0.988 to 0.998. However, with L_{lcm} method, we note a significant drop in accuracy.

Input Images: Focusing on T9 and MeerCRAB3, the NRD input yields the best performance model with an accuracy of 99.2%.

Network architectures: With deeper networks (MeerCRAB2 and MeerCRAB3), we obtain a higher performance with an accuracy of 98.6% & 99.2% respectively.
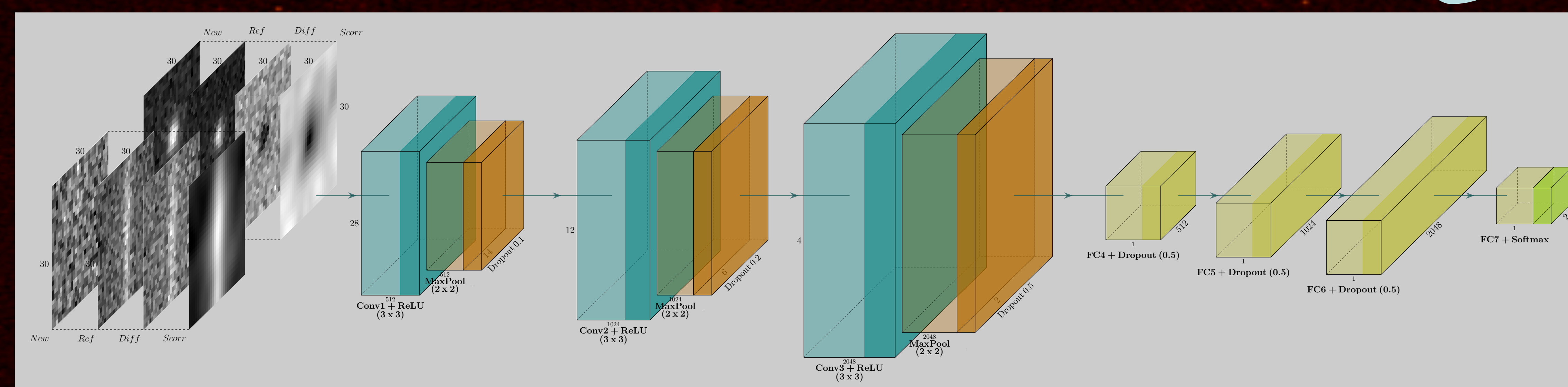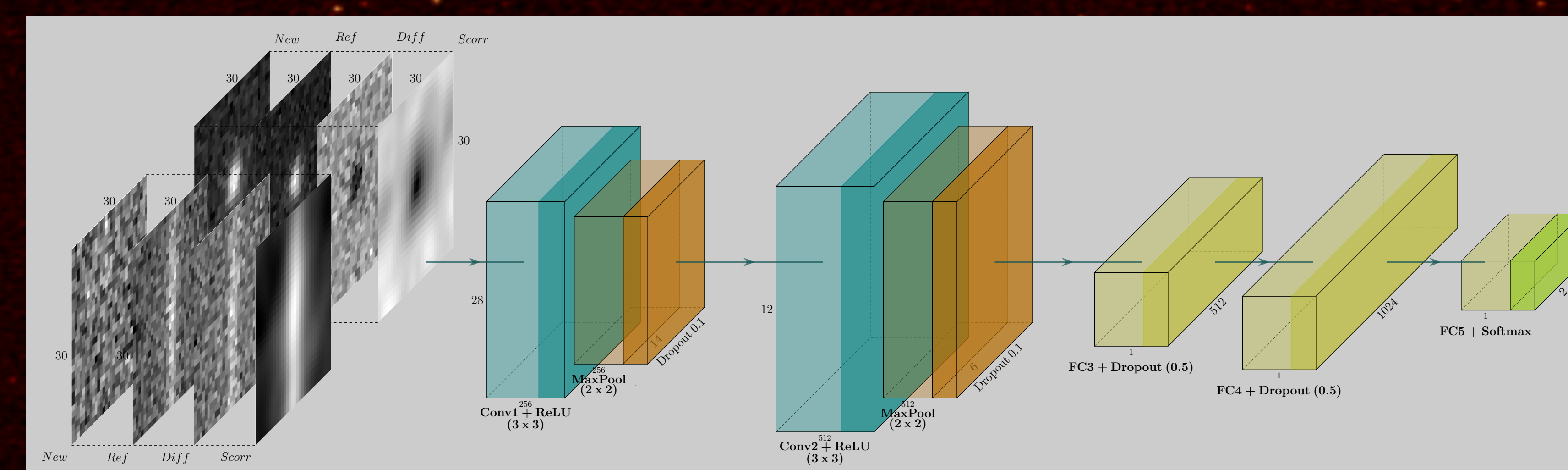
Methods of labelling	Precision	Recall	Accuracy	MCC
MeerCRAB1				
L_{lcm}	0.96	0.96	0.960	0.920
T8	0.98	0.98	0.980	0.958
T9	0.98	0.98	0.979	0.958
T10	0.99	0.99	0.991	0.983
MeerCRAB2				
L_{lcm}	0.97	0.97	0.967	0.936
T8	0.99	0.98	0.977	0.953
T9	0.99	0.99	0.986	0.973
T10	0.99	0.99	0.994	0.988
MeerCRAB3				
L_{lcm}	0.97	0.97	0.968	0.936
T8	0.99	0.99	0.988	0.976
T9	**0.99**	**0.99**	**0.992**	**0.984**
T10	1.00	1.00	0.998	0.995