

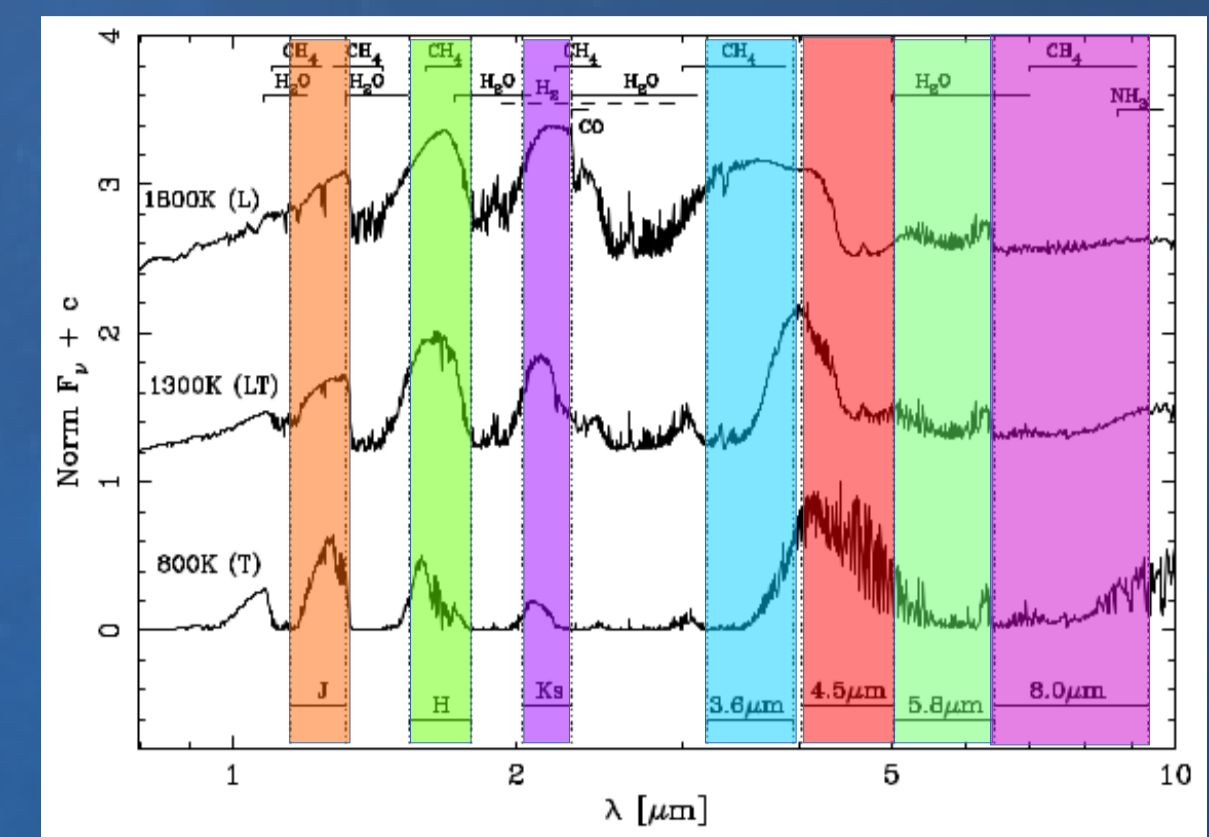


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## INTRODUCTION

The advent of large all-sky photometric surveys, each identifying millions of new objects, necessitates automated techniques for classification. The need for handling multidimensional feature spaces (wherein different classes can be clearly distinguished) has led to the introduction of machine learning algorithms for this purpose.<sup>1</sup> In this work, we attempt to create an ensemble classifier by applying simple machine learning techniques such as the k-nearest neighbour (k-NN) method and the neural network (NeuN) algorithm for identification of elusive objects such as brown dwarfs, which are rarely observed despite being theoretically predicted to be in abundance.<sup>2</sup> Brown dwarfs fall under three spectral types, L, T, and Y. Their emission peaks in the infrared with a distinctive spectral energy distribution arising from strong molecular absorption features.<sup>3</sup> Most of the brown dwarf searches till date have used generic colour cuts to identify candidates.<sup>4,5</sup> An exception is Marengo & Sanchez (2009), who present a statistical method for the photometric search of brown dwarfs using the k-NN method. Here, we use two variants of k-NN, as well as the NeuN algorithm, to identify brown dwarf candidates using the photometric colours of known brown dwarfs. We initially check the efficiencies of these three classification techniques, both individually and collectively, on known objects. This is followed by their application to three regions in the sky.



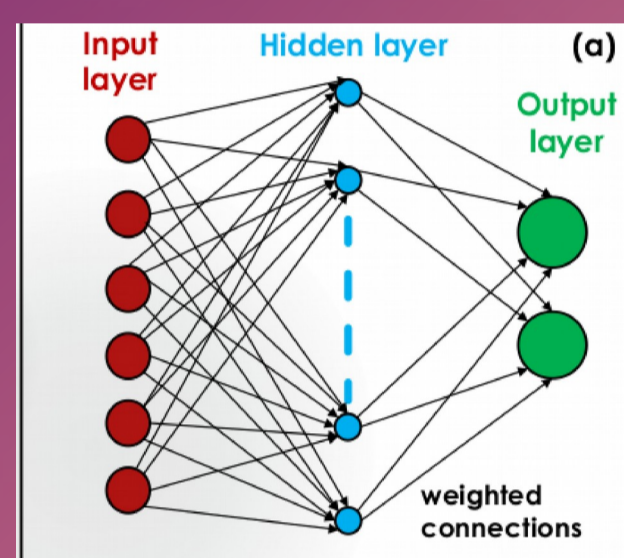
**Figure 1.** Model spectra of brown dwarfs. The main molecular absorption features in the near- and mid-IR range are marked, as well as the 2MASS and IRAC bandpasses.<sup>6</sup>

## CLASSIFICATION SCHEMES

The classification methods used in this study are NeuN and two variants of k-NN, one of which is identical to the one used by Marengo & Sanchez (2009). In addition to these three, we have also created an ensemble classifier, which factors in outputs from all the individual classifiers and makes the final decision on the basis of a majority vote. The three methods are pictorially depicted below.

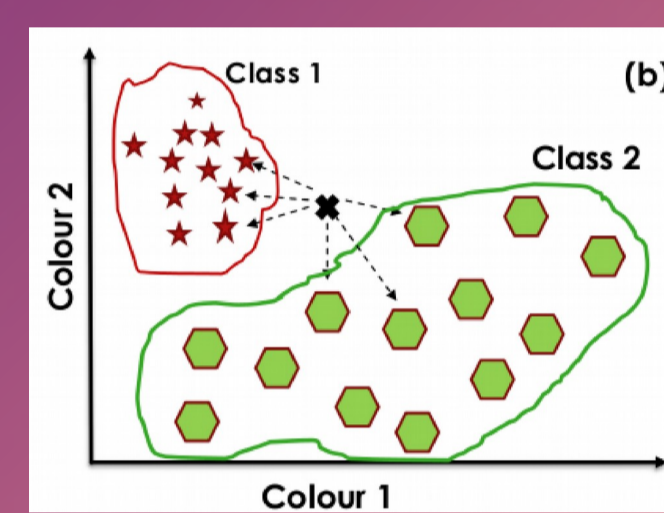
### Neural Networks (NeuN)

A NeuN is constructed using layers of individual processing units, called neurons or nodes. The input features for classification correspond to the nodes in the input layer, while the number of nodes in the output layer is decided by the number of output classes.



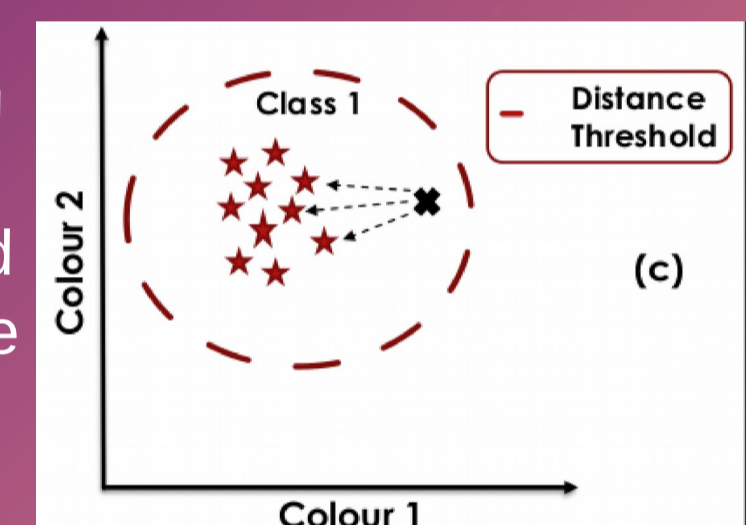
### k-Nearest Neighbour approach to Classification (k-NN-C)

The class of an object is decided based on its distance to a specific class (either brown dwarf or background) of templates, where distances are defined in a multidimensional colour space.



### K-Nearest Neighbour Threshold Distances (k-NN-TD)

The k-NN distance of each test object is calculated from a training sample consisting entirely of brown dwarfs, and objects whose k-NN distance is within a certain defined threshold are classified as brown dwarfs.



### Ensemble Classifier

## DATA USED

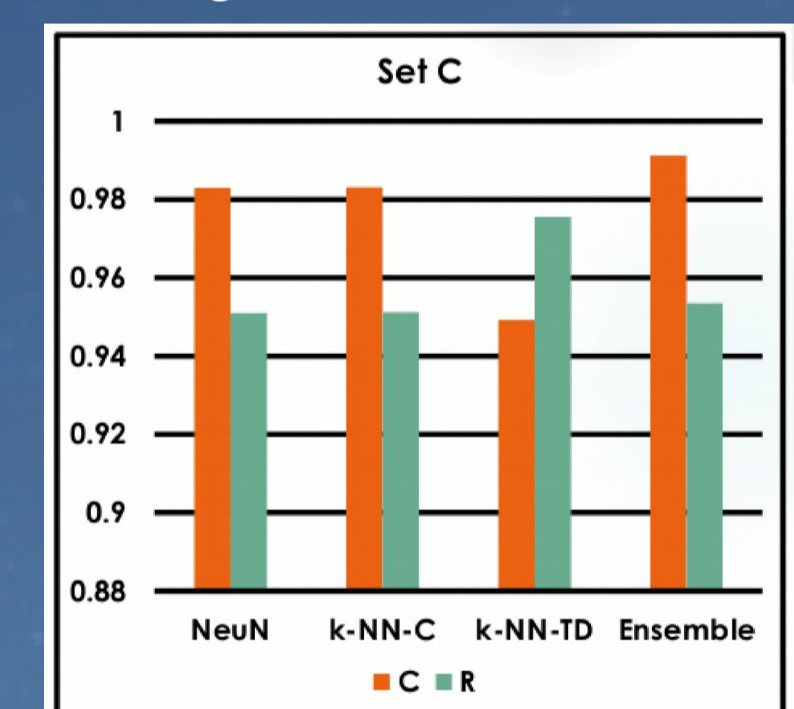
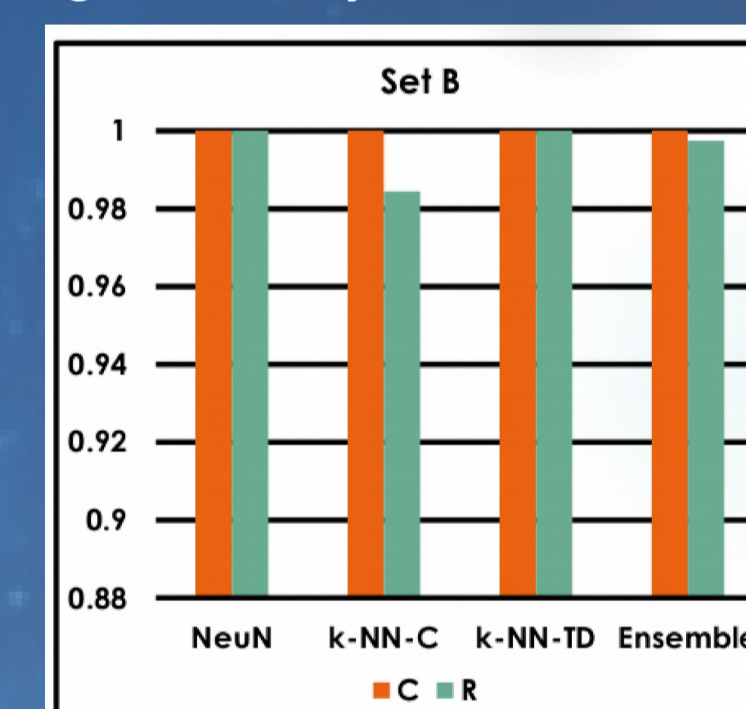
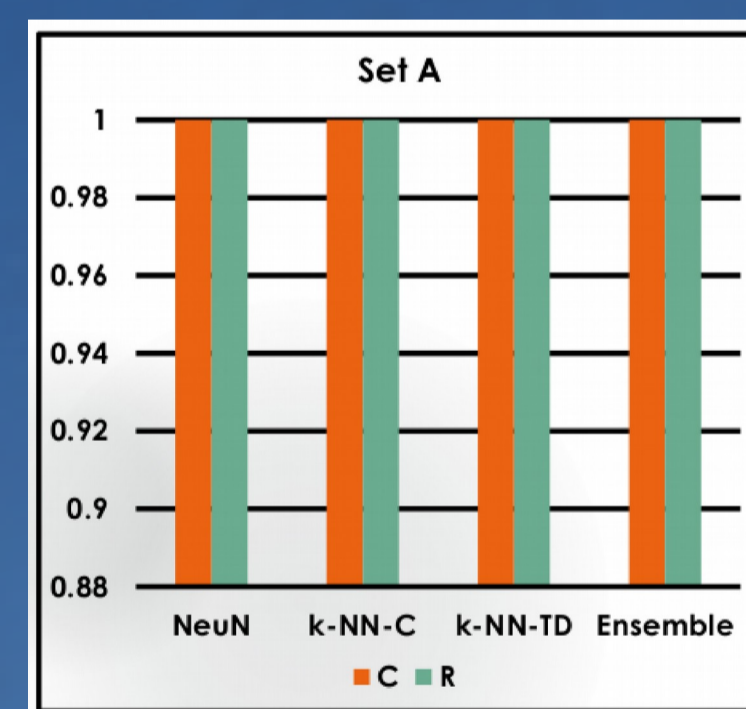
Data was taken from WISE W1, W2, W3 and 2MASS J, H, K<sub>s</sub> bands. Six colours were selected based on the spectral characteristics of brown dwarfs in the WISE and 2MASS filters.<sup>4,6</sup> They are listed below.

Colour	Characteristic
W1 - W2	Methane absorption in W1
W2 - W3	Methane absorption in lower bands
J - H	H <sub>2</sub> O absorption in J
J - W1	H <sub>2</sub> O absorption in J
J - W2	H <sub>2</sub> O absorption in J
J - K <sub>s</sub>	Presence of methane

**Table 1.** Photometric colours used as features for brown dwarf classification, using WISE and 2MASS filters.

## OPTIMAL TRAINING SETS

Different training sets are created by combining templates from various brown dwarf and background object catalogues. Only those background objects have been included in the training sets, which were felt to have an effect on the classification on brown dwarfs and, hence, were likely contaminants. The efficiencies for the sets, and for different methods, are then calculated by using completeness (C = fraction of true positives) and rejection efficiency (R = fraction of true negatives) as the validation metrics. In the 2-class classification, both NeuN and the ensemble classifier emerge as the best methods. The three optimal training sets were named as A, B and C. Set A contains brown dwarfs and background objects taken from the ALLWISE catalog. Set B also includes NLS1 galaxies as background objects. Set C contains YSOs, Red Giants, A- & K- type stars, in addition to the NLS1 galaxies in the background class but does not contain the background objects from the ALLWISE catalog.



**Figure 2.** Completeness (C) and Rejection efficiency (R) of the three optimum training sets A, B, and C

## TESTING ON REGIONS IN SKY

The methods and optimal training sets are applied to three regions in the sky: Serpens, Hercules, and Lyra. Of these, Serpens and Hercules have known brown dwarfs, previously identified by WISE. The NeuN classifier performs relatively better than the k-NN methods in the three regions, identifying all the previously known dwarfs. This is followed by the ensemble classifier. The two k-NN methods do not fare as well, with k-NN-C being the better of the two. Of all the training sets used, training set C performs best on sources from given regions on the sky. **59, 6 and 15 brown dwarf candidates were identified in the Serpens, Hercules and Lyra regions respectively.** A search for counterparts in the SIMBAD and Gaia databases was also carried out for the brown dwarf candidates from each region. **This led to the identification of one of the candidates in the Serpens region as a brown dwarf that was not part of the brown dwarfs identified by WISE.**

Training Sets		Set A			Set B			Set C		
Region	Method	N <sup>a</sup>	Known Dwarfs KR <sup>b</sup>	RR <sup>c</sup> (percent)	N <sup>a</sup>	Known Dwarfs KR <sup>b</sup>	RR <sup>c</sup> (percent)	N <sup>a</sup>	Known Dwarfs KR <sup>b</sup>	RR <sup>c</sup> (percent)
Serpens (9° x 4°)	NeuN	16	5/5	99.9	7	5/5	99.9	20	5/5	99.9
	Ensemble	47	4/5	99.8	8	5/5	99.9	27	5/5	99.9
Hercules (2° x 2°)	NeuN	4	3/3	99.9	3	2/3	99.9	5	3/3	99.8
	Ensemble	3	1/3	99.9	1	1/3	99.9	7	3/3	99.7
Lyra (2° x 2°)	NeuN	7	-	99.8	1	-	99.9	2	-	99.9
	Ensemble	9	-	99.8	1	-	99.9	9	-	99.8

**Table 2.** Results from testing on the 3 regions (<sup>a</sup>N- Number of brown dwarfs; <sup>b</sup>KR- Ratio of known brown dwarfs; <sup>c</sup>RR - Rejection ratio)

## CONCLUSIONS

- NeuN and k-NN methods have been used for classifying astronomical objects based on their photometric colours. Although the methods are general and can be applied to select any specific kind of astronomical objects, we have applied it to the specific case of brown dwarfs.
- We apply the methods and optimal training sets to three regions in the sky: Serpens, Hercules, and Lyra. The nature of the identified brown dwarf candidates can be verified through follow-up spectroscopic studies.
- These methods of multidimensional classification based on photometric colours are expected to significantly downsize the candidate sample for follow-up studies, as compared to traditional colour and magnitude diagrams or threshold cuts.