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A machine-learning approach for classifying low-mass X-ray binaries based on their compact object nature

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ABSTRACT

Low-mass X-ray binaries (LMXBs) are binary systems where one of the components is either a black hole or a neutron star and the other is a less massive star. It is challenging to unambiguously determine whether an LMXB hosts a black hole or a neutron star. In the last few decades, multiple observational works have tried, with different levels of success, to address this problem. In this paper, we explore the use of machine learning to tackle this observational challenge. We train a random forest classifier to identify the type of compact object using the energy spectrum in the energy range 5–25 keV obtained from the *Rossi X-ray Timing Explorer* archive. We report an average accuracy of 87 ± 13 per cent in classifying the spectra of LMXB sources. We further use the trained model for predicting the classes for LMXB systems with unknown or ambiguous classification. With the ever-increasing volume of astronomical data in the X-ray domain from present and upcoming missions (e.g. *Swift*, *XMM–Newton*, *XARM*, *Athena*, and *NICER*), such methods can be extremely useful for faster and robust classification of X-ray sources and can also be deployed as part of the data reduction pipeline.

Key words: X-rays: binaries – methods: data analysis – methods: statistical.

1 INTRODUCTION

Low-mass X-ray binaries (LMXBs) are binary systems where one of the components is a black hole (BH) or a neutron star (NS) and the other component is a less massive star, usually a main sequence, a white dwarf, or an evolved star of $M < 1 M_{\odot}$. Some LMXBs combine long periods of quiescence (from a few months to decades) with short periods where the source is in outburst that lasts from days to years. In quiescence, LMXBs are very faint ($\sim 10^{30}–10^{33}$ erg s^{−1}), while during outbursts LMXBs increase several orders of magnitude their fluxes (see e.g. McClintock & Remillard 2006).

The energy spectra of LMXB systems are described by two main components: a thermal component and a hard component. The thermal component is usually described by a multicolour disc blackbody (Mitsuda et al. 1984) and it is thought to be produced by an accretion disc (Shakura & Sunyaev 1973). The hard component is thought to be produced by the so-called corona, which is a region of hot plasma around the compact object (e.g. Sunyaev & Titarchuk 1980). This component is usually described by a thermal Comptonisation model (e.g. Titarchuk 1994; Done, Gierliński & Kubota 2007). The contribution of these components to the X-ray emission of LMXBs varies during an outburst, modifying its spectral

and timing properties (e.g. van der Klis 1989; Méndez & van der Klis 1997; Homan & Belloni 2005; Remillard & McClintock 2006; Belloni 2010; Tetarenko et al. 2016). LMXBs show different spectral states during an outburst based on its spectral and timing properties (e.g. Homan & Belloni 2005; Remillard & McClintock 2006; Belloni 2010). The two main states are the high/soft state (HSS) and low/hard state (LHS). In the HSS, the accretion disc is thought to extend down to the surface of the NS or the last stable orbit (if the compact object is a BH). Because of that the energy spectrum is dominated by the accretion disc, which is described by the thermal component. In the LHS, the disc is thought to be truncated at larger radius than that in HSS, so the spectrum is dominated by the corona, usually described by the Comptonised component. Between these two spectral states, the source can show different intermediate states with spectral and timing properties between the properties of the LHS and HSS. The evolution along these states can be well studied with the hardness–intensity diagram (HID; see e.g. Homan et al. 2001) and the colour–colour diagram (CCD; e.g. Hasinger & van der Klis 1989; van der Klis 1989).

One of the fundamental questions when studying LMXBs is whether the compact object in the binary is a NS or a BH. The presence of one or the other can have a significant impact on the physical interpretation of the phenomenology observed. With the large-scale sky surveys and transient search programmes [e.g. *INTEGRAL/JEM-X* (Lund et al. 2003), *Swift/BAT* Transient Monitor

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(Krimm et al. 2013), *MAXI* (Matsuoka et al. 2009), *eROSITA* (Merloni et al. 2012)], the sample of LMXBs is ever increasing. Such newly detected transient sources are usually characterised by their fast variation (days) of luminosity by orders of magnitude. The early identification of the nature of the compact object is very important for the community to be able to trigger expensive (and usually difficult to plan) observing campaigns (Middleton et al. 2017). These campaigns, in most cases, can only be triggered if the nature of the compact object is known. There are only a few methods that allow the community to unambiguously identify the nature of the compact object: coherent pulsations (Patruno & Watts 2012, and references therein) and presence of thermonuclear bursts (for reviews, see e.g. Lewin, van Paradijs & Taam 1993; Cumming 2004; Galloway et al. 2008; Strohmayer et al. 2018), which determines unambiguously that the compact object is a NS, and the estimation of the mass based on the mass function of the system. Apart from that, one can only estimate the nature of the compact object by comparing its X-ray timing and spectral properties and X-ray–radio correlation with those of other known sources.

As we mentioned above, the energy spectra of LMXB systems are described by a thermal component and the Comptonised component. In addition, NS LMXBs also show emission from the surface of the NS and the so-called ‘boundary layer’; this component is generally described by a blackbody (e.g. Mitsuda et al. 1984; Di Salvo et al. 2000; Gierliński & Done 2002; Lin, Remillard & Homan 2007). It is also possible to use the presence of this additional component on the NS LMXB energy spectra to distinguish between BH and NS systems. Probably this is the most commonly used method when a new system is discovered, and at the same time it is probably one of the most unreliable methods. See, for example, the case of XTE J1812–182 (Markwardt, Pereira & Swank 2008; in ’t Zand et al. 2017; Goodwin et al. 2019), *MAXI* J1810–222 (Maruyama et al. 2018; Negoro et al. 2019), or *MAXI* J1807+132 (Shidatsu et al. 2017). Following the detection of a new transient LMXB, the individual spectra obtained typically do not result in statistically significant deviations between the different spectral models in order to infer the nature of the corresponding compact object.

The identification of the compact object can also be done based on the X-ray timing properties of the system. As we mentioned earlier, if coherent pulsations are found, we can determine unambiguously that the system hosts a NS (see Patruno & Watts 2012, and references therein). The presence of quasi-periodic oscillations (QPOs) at frequencies between 300 and 1200 Hz (the so-called kilohertz QPO, se.g. van der Klis 2006; van Doesburgh, van der Klis & Morsink 2018) strongly suggests that the compact object is a NS too. However, the presence of the low-frequency QPOs in the mHz to 50 Hz range does not always unambiguously pinpoint the nature of the system (Klein-Wolt & van der Klis 2008). Both BH and NS are also similar in terms of broad-band noise up to 500 Hz (Klein-Wolt & van der Klis 2008). Above 500 Hz, the broad-band noise of BH systems decreases while NS systems can show broad-band noise up to higher frequencies (Sunyaev & Revnivtsev 2000). In terms of radio emission, BH systems are generally brighter than NS systems in the radio band, when observed at comparable X-ray luminosity (Fender & Kuulkers 2001; Fender 2006; Migliari & Fender 2006; Corbel et al. 2013; Fender & Gallo 2014).

The nature of the compact object can also be identified by estimating the mass function of the system and measuring, estimating, or assuming the mass of the companion star. The mass function only gives a lower limit of the mass of the compact object given uncertainties in the inclination of the system. If the compact object is $> 4\text{--}5 M_{\odot}$, then it is usually agreed that system contains a BH

(e.g. Casares, Charles & Naylor 1992; McClintock et al. 2001; Orosz 2003; Casares 2007; Muñoz-Darias, Casares & Martínez-Pais 2008). If it is of the order of $2 M_{\odot}$ or less, then it is most probably a NS (Orosz 2003; Lattimer & Prakash 2004, 2007; Casares 2007; Ziōłkowski 2008; Demorest et al. 2010; Lattimer 2012).

In some rare occasions, the mass estimate is in the $2 M_{\odot} < M < 4 M_{\odot}$ range. In this case, it is not possible to determine unambiguously the nature of the compact object. GRO J0422+32 gives a good example of the limitations of this method. Gelino & Harrison (2003) estimated the mass of GRO J0422+32 to be $3.97 \pm 0.95 M_{\odot}$, and therefore a BH identification. However, about 10 yr later Kreidberg et al. (2012) explored possible systematic underestimations of the inclination of X-ray binary systems, which can increase the mass of the compact objects. They found this was the case of GRO J0422+32 and, taking into account this underestimation, they obtained a mass of $2.1 M_{\odot}$, suggesting that GRS J0422+32 was instead a NS system.

However, it is not always possible to have an estimation for the mass of the companion star and, as a result, estimate the mass function of the system. Despite this fact, it is still possible to estimate the mass function of the compact object. Casares (2015) found a correlation between the full width at half maximum of the $H\alpha$ line of the accretion disc and the velocity semi-amplitude of the companion star that, combined with supplementary information on orbital periods, can be used to estimate the mass function of the compact object from single-epoch spectroscopy. Another correlation between the mass ratio of the binary system and the ratio of the double-peak separation to the line width can be used to estimate the mass function of the system (Casares 2016) and, from there, try to determine the nature of the compact object.

All the methods of classifying LMXB sources that have been employed so far have had their own drawbacks. One technique that is yet to be explored to classify LMXBs is the use of machine-learning (ML) algorithms. ML algorithms have been successfully used to solve problems in various domains of astronomy. They have been used to identify the furthest quasars in the Universe (Mortlock et al. 2011), classify galaxies based on their morphology (Storrie-Lombardi et al. 1992; Bazell & Aha 2001; de la Calleja & Fuentes 2004; Banerji et al. 2010), to detect small near-Earth asteroids (Waszczak et al. 2017), and even for hunting exoplanets (Thompson et al. 2015; Pearson, Palafox & Griffith 2018). ML has also been applied in the X-ray domain by Huppenkothen et al. (2017) to classify light curves of the unusual BH X-ray binary GRS 1915+105. An effort to distinguish between different types of X-ray binaries has been reported by Gopalan, Vrtilik & Bornn (2015), where they use a three-dimensional coordinate system comprising of colour–colour–intensity diagrams to find clusters of data that can distinguish between BH and NS.

In this work, we explore whether ML applied to the X-ray energy spectra of LMXBs can be used to identify the nature of the compact object. In order for ML algorithms to work, a large data base of classified data is needed to develop a robust classification model. For this reason, we use the full archive from the *Rossi X-ray Timing Explorer (RXTE)* mission (Bradt, Rothschild & Swank 1993). This is probably the largest data base today of X-ray observations of LMXBs, providing us with more than 8500 observations from 33 NS systems and more than 6000 observations from 28 BH systems.

The outline of the paper is as follows. Section 2 describes the structure and composition of the data used in this work. In Section 3, we explain the process of choosing an ML algorithm for classifying

LMXBs along with a small description of the chosen algorithm – the random forest (RF). This is followed by different methods employed and their results in Section 4. In Section 5, we analyse the results based on different factors that govern the classification and predict the classes for sources with unknown classification. Summary and future scope of this work are presented in Section 6.

2 DATA REDUCTION AND PREPARATION

We used data from the Proportional Counter Array (PCA; Glasser, Odell & Seufert 1994) instrument aboard the *RXTE*. The PCA is an array of five proportional counters units (PCUs) with a total collecting area of 6500 cm²; each PCU has an energy range of 2–60 keV. We selected a total of 61 sources that are classified as BH or NS binaries, depending on the nature of the compact object. We chose those sources that have been extensively studied in the past and the classification is well known and consistent across different studies and catalogues (see e.g. Corral-Santana et al. 2016; Tetarenko et al. 2016, for BH). After source selection, we obtain all data from pointed observations corresponding to these sources from the *RXTE* archive.¹

To calculate X-ray colours, we use the 16-s time-resolution Standard 2 mode data. For each of the five PCA detectors (PCUs), we calculate a soft colour and a hard colour, which are defined as the ratio between the count rate in the 6.0–16.0 and 2.0–6.0 keV bands, and the ratio between the 16.0–20.0 and 2.0–6.0 keV bands. We also calculate the intensity defined as the count rate in the 2–20 keV band. To obtain the count rates in these exact energy ranges, we make a linear interpolation between all the PCU channels. We then carry out dead-time corrections, we subtract the background contribution in each band using the standard bright source background model for the PCA (version 2.1e1), and we remove instrumental drop-outs to obtain the colours and intensity for each time interval of 16 s. It is important to take into account that the *RXTE* gain epoch changes with each new high voltage setting of the PCUs (Jahoda et al. 2006). We normalized our data to the Crab (method introduced by Kuulkers et al. 1994) in order to correct for this effect and the differences in effective area between the PCUs.

For each observation, we obtain the background, response, and the spectrum files from which we extract the count rate values of the desired energy spectrum range in a text file using the XSPEC software (Arnaud 1996). We then reject all observations that have a net count rate less than 5 counts per second in order to avoid low signal-to-noise spectra.

For each observation, we used 43 channels within the energy range of 5–25 keV. ML algorithms require each observation to be of the same size; hence, we keep the number of channels fixed to 43.

We use these 43 count rate values directly as an input vector for the ML algorithm. Due to variations in the sensitivity of particular channels with time, energy ranges tend to vary a little bit for each spectrum (Jahoda et al. 1996, 2006). The interstellar absorption N_{H} can vary from source to source, and therefore adds another variable that the ML algorithm must take into account. We found that in practice, ignoring data below the 5 keV range to avoid the effect of N_{H} produced higher accuracy in classification. We chose the upper bound as above the energy value of 25 keV the instrument efficiency begins to deteriorate and the corresponding values contain minimal information about the spectrum.

We also choose to ignore other potential contributions or effects on the spectra as otherwise it would result in further reduction of our already small sample of spectra. Furthermore, the objective of using ML is to identify intrinsic characteristics of the spectra belonging to two classes and accounting for these effects would add more human biases. Among the potential contributions and/or effects, we ignored that from possible absorption/emission lines on top of the X-ray continuum (i.e. the ~ 6.5 keV iron line). This is because such lines generally contribute only a few percentages of the total flux, their strength varies differently between sources, between states of a given source, and in most cases are not resolved given the low spectral resolution of the *RXTE*/PCA data. We also did not take into account the effects of the different source inclination. This is because little is known about the inclination, and generally the uncertainties are very large (Muñoz-Darias et al. 2013; Motta et al. 2015).

In the final data set, we have a fairly balanced representation of the two classes with 8669 observations from 33 sources identified as NS LMXBs (58 per cent) and 6216 observations from 28 sources identified as BH LMXBs (42 per cent). In Fig. 1, we show the number of observation per source for each class in the data set. As can be observed, a few sources have >1000 observations while some have <20 observations.

3 ALGORITHM SELECTION AND DESCRIPTION

ML is a branch of computer science that consists of algorithms that can learn to identify patterns in the data without any prior specification of a rule or model. By learning from the information in the data, an ML algorithm tries to approximate an underlying model that can define the data. Such models are used for handling various problems like classification, regression, clustering, etc. An algorithm tries to approximate these models in its ‘training phase’ and based on the process it uses to approximate these models it is divided into two categories: supervised and unsupervised techniques.

For implementing an ML method, the data set should contain a specific number of features for each input object. In the supervised training method, each set of input features corresponds to a label or a target value. The data set is divided into train, validation, and test sets. The model is trained using the former, and then validated using the validation set. Multiple models with different initial settings are trained on the first set, and the best one is selected using the validation set. Supervised ML problems can further be divided into two types – classification and regression. Simply put, when the expected outcome is a real-valued number, it is considered as a regression problem (Ramírez, Fuentes & Gulati 2001; Firth, Lahav & Somerville 2003; Nesseris & García-Bellido 2012) whereas when the objective is to categorize data, it is known as a classification problem (Bazell & Aha 2001; McGlynn et al. 2004; Ball et al. 2006; Zhao et al. 2007). In the unsupervised type of ML techniques, there is no requirement for a predefined label/class, and the algorithm tries to understand the relation between the input features without the help of the user. Some common examples of unsupervised learning include clustering tasks (Feitzinger & Galinski 1987; Wagstaff & Laidler 2005; Rebbapragada et al. 2009), dimensionality reduction (Hojnacki et al. 2007), estimating the density function (Ferdosi et al. 2011), and association.

In this work, we approach the problem of classifying an X-ray spectrum into either a BH or a NS. This is a supervised binary classification problem. There are several ML algorithms that can be used for handling this type of binary classification problem. As per

¹<https://heasarc.gsfc.nasa.gov/cgi-bin/W3Browse/w3browse.pl>

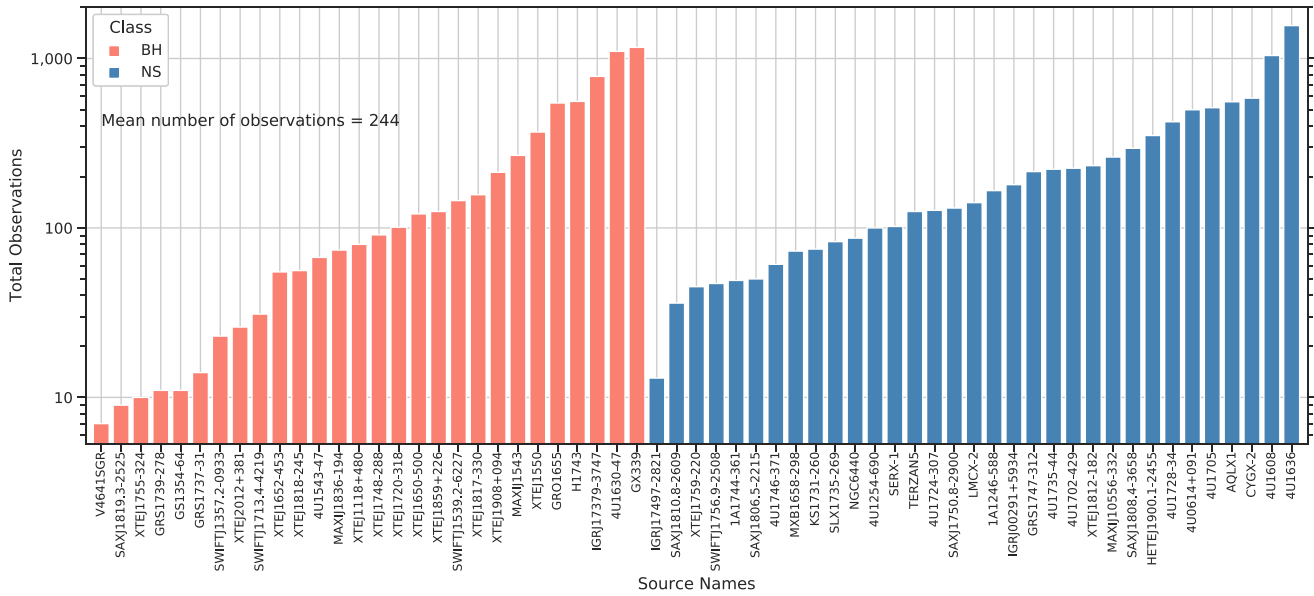


Figure 1. Source-wise distribution of data on BH and NS classes. The mean is approximately 244 observations with some sources having 1000+ observations while others having less than 20. The list of individual sources along with their total number of observations and class labels can be also found in Table A2.

the ‘no free lunch theorem for optimisation’ (Wolpert & Macready 1997), there is no one particular algorithm that excels in all scenarios. However, there are a few points the user should consider while selecting the right ML algorithm. In our case, the first criterion is accuracy. The algorithm that can provide the highest percentage of correct classifications is usually the most favourable.

One of the weaknesses of using ML methods is that they are a ‘black-box’ when the user wants to understand the decision-making process that leads to a given result. This property of an ML algorithm is known as interpretability. Sometimes the most accurate algorithms are the least interpretable or vice versa. Therefore, there is usually a trade-off between the two criteria for selecting the best algorithm (Nakhaeizadeh & Schnabl 1997). It is worth mentioning that it is possible to study the decision-making process of an algorithm; however, the nature of the data can make it very difficult (or virtually impossible) to understand the process. In cases where the data have features (or input vector to the ML algorithm) that have some direct physical meaning (for example, temperature, mass, etc.), it is possible to draw correlations or understand which physical feature has the most significant contribution to the decision-making process. In the problem studied in this paper, data consist of count rate values corresponding to a certain energy range. Therefore, it is very difficult to visualize and/or understand the decision-making process. Therefore, we decided that it was more favourable to choose an algorithm that is more accurate, even if it compromised the interpretability.

In this work, we experimented with the following algorithms:

(i) **Classification and Regression Trees (CART) or more commonly known as Decision Trees** (Breiman et al. 1984): use a tree-like structure to map the input vector to the target values. Based on the target values, they can be either classification trees or regression trees.

(ii) **Random Forest (RF)** (Breiman 2001): is an ensemble method that combines the output of several decision trees to improve on the prediction of a single tree. As we will see in Section 3.1 this method has the highest accuracy compared to the other algorithms

and therefore is our algorithm of choice. We will talk about it in more detail later in Section 3.0.1.

(iii) **XGBoost (XGB)** (Chen & Guestrin 2016): is another ensemble method that implements ML algorithms in a gradient boosting framework (Mason et al. 2000) to improve efficiency and speed.

(iv) **Logistic Regression (LR)** (Cox 1958): is a multivariate analysis model that predicts the probability of membership to any class based on the values of some predictor variables; these variables are not constrained to follow a given (normal) distribution, not even be continuous.

(v) **k-Nearest Neighbours (KNNs)** (Cover & Hart 2006): is a non-parametric classification technique that works on the following simple principle: Given a query for prediction, it finds the k-closest neighbours to the data point in the training sample by calculating the Euclidean distance from every point and then assigns the class that is the most common among its k-nearest neighbours.

(vi) **Support Vector Machines (SVM)** (Cortes & Vapnik 1995): is a type of kernel-based algorithm that builds a set of hyperplanes in the high-dimensional feature space such that they have the maximum possible distance from the nearest data point of any class, thus optimizing the separation between the different classes in the data.

For further reference on the detailed workings of these algorithms, see Ivezić et al. (2014), an astronomy-oriented textbook for ML.

We chose these algorithms as they fall into the category of traditional ML algorithms that are usually known to show satisfactory performance even with a limited amount of data. They also have significantly lower execution times as compared to the widely popular deep learning methods (see for e.g. Kotsiantis, Zaharakis & Pintelas 2007).

3.1 Random Forest

Random Forest is an ensemble technique that is used to boost the prediction made by an individual decision tree (Breiman 2001). A

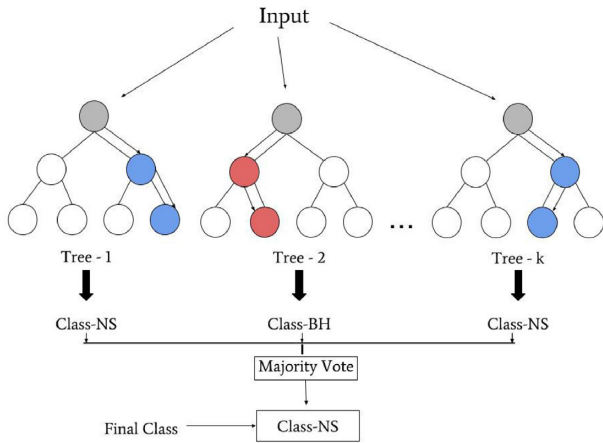


Figure 2. Illustration of the decision-making procedure in an RF algorithm.

decision tree is one of the most intuitive yet powerful ML algorithms (Breiman et al. 1984). A decision tree is made up of branches of nodes, where sets of if-this-then-that rules are applied to the features of the input data, and based on the result, lead down one of the branches of the tree. The final layer of nodes, also known as leaf nodes, contains a predicted class label that is compared to the expected class for a particular input vector. Although the decision tree algorithm has proven to be very efficient (see for e.g. Vasconcellos et al. 2011), a decision tree, if improperly trained, can at times overfit the data (chapter 3 in Mitchell 1997). The idea behind RF is to combine the decisions of several such trees to improve upon the decision of a single overtrained tree. Taking a majority vote over the decision of all the trees helps in reducing the variance of the predictions (Breiman 2001). The probability of a source belonging to one class or the other is also calculated in a similar way, i.e. by dividing the number of trees that predicted the same class by the total number of trees. The basic working of an RF algorithm is explained below:

- (1) From a total number of K input features, the algorithm chooses a number I such that $I \ll K$.
- (2) Using bootstrap sampling, the algorithm chooses a training set for a tree by selecting a subset from the complete training data. It keeps the remaining data for validating the predictions.
- (3) The algorithm chooses I random features at every node of the tree and then calculates the most optimal split for the training set using these features.
- (4) The algorithm grows every tree to its maximum depth without any pruning (unlike a solitary decision tree that is pruned after growing fully to prevent overfitting (see Breiman et al. 1984)).
- (5) The algorithm then repeats the above step to generate many such trees.
- (6) After the training is completed, the algorithm uses a majority vote to predict the class of the input data. To calculate the majority vote for a given input vector, the algorithm selects the class that was predicted by the majority of individual trees. To calculate the probability/confidence of the prediction, the algorithm uses the ratio of trees that predicted the particular class to the total number of trees.

A decision tree algorithm works from top to bottom (see Fig. 2) and usually chooses a variable at each step that optimally splits the set. Depending on the particular splitting algorithm used, the selection process of the variable varies. Here, we use the default gini impurity method (Breiman et al. 1984) that is a measure of the likelihood of an

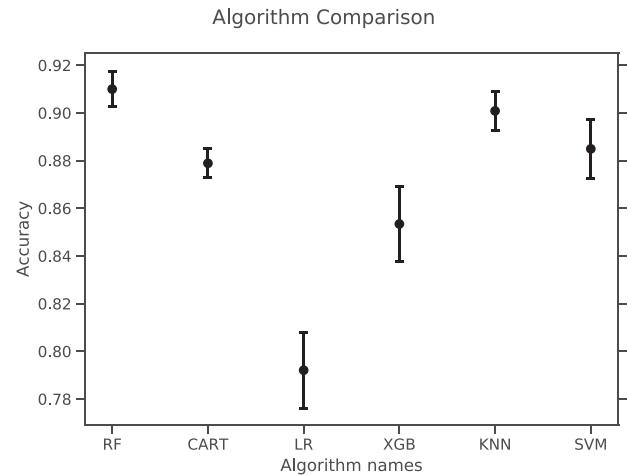


Figure 3. Comparison of the performance of different ML algorithms using the 10-fold cross-validation process. The algorithms on the x -axis (from left to right) are RF, Decision Tree (CART), LR, XG-Boost, KNNs, and Support Vector Machines. The RF performs the best with an overall accuracy of 91 ± 2 per cent.

incorrect classification of a randomly chosen element, if the element was randomly labelled according to the distribution of labels in the data set.

We illustrate the decision-making process of an RF algorithm in Fig. 2. We implement the RF algorithm using the `scikit-learn`² (Pedregosa et al. 2011) library of PYTHON. We use grid search combined with cross-validation to find the best hyperparameters for the algorithm. Hyperparameters are a set of parameters defined prior to the training process that are used to tune the performance of the ML algorithm. The optimal hyperparameters obtained were as follows:

- (i) `Min_samples_leaf` = 3 (the minimum number of samples required to be at the leaf node).
- (ii) `Min_samples_split` = 8 (the minimum number of samples required to split an internal node).
- (iii) `Max_features` = 2 (the number of features to consider when looking for the best split).
- (iv) `N_estimators` = 1000 (the number of trees in the forest).

3.2 Comparison of algorithms

For selecting the best classification method, we train and test different algorithms and compare them using ‘accuracy’ as a metric, which is defined as the ratio of the number of observations correctly classified to their class (NS or BH) to the total number of observations.

To compare the algorithm, we first split the data set consisting of 14885 observations into training and test sets and use k -fold cross-validation technique (Burman 1989), in which we divide the data set into k even samples. Then, we use one sample as a test set while training on the remaining $k - 1$ samples. We repeat this process for each of the k samples in the process covering the entire data set. We use 10-fold cross-validation ($k = 10$) along with the default hyperparameters for each algorithm. Results of the 10-fold cross-validation and comparison between the different algorithms are presented in Fig. 3. We find that the RF algorithm performs the best among all the selected methods, giving the highest accuracy

²<https://scikit-learn.org/stable/>

Table 1. Performance of the algorithm for the two classes using the traditional train–test split method.

Class	No. of test obs.	Correctly classified	Misclassified	Accuracy (per cent)
NS	867	814	53	94
BH	622	545	77	88
Total	1489	1359	130	91

of 91 ± 2 per cent. Therefore, in the following sections we only report on the results of the classifications obtained using the RF algorithm.

4 METHODS AND INITIAL RESULTS

We apply the RF algorithm with the best combination of hyperparameters to the data set described in Section 2. Since the data set contains 14 885 observations for 61 individual X-ray sources, each source is represented by multiple observations taken at different times. Given that the LMXBs studied here are variable in nature, different observations for the same source could be sampling a different physical spectral state (i.e. different geometrical configurations). Therefore, the classification of the energy spectra of LMXBs can be treated as any other typical ML binary classification problem where each observation is considered independent of the others. However, due to the nature of the problem and the limitations of our data (e.g. time-variability factors in the data, correlations between spectra of the same source taken at different times, and unequal number of observations for different sources), we had to use different strategies to train the model and evaluate its performance. We used the following:

(i) Traditional train–test split (observation-wise splitting): In this approach, the 14 885 spectra are randomly split into a training set and a test set consisting, respectively, of 90 per cent and 10 per cent of the observations. Here, we assume that each observation is independent of the rest, meaning that there are no correlations between different observations for the same source.

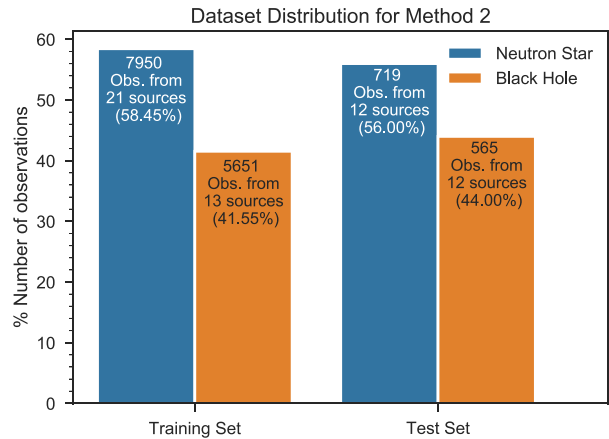
(ii) Source-wise splitting: Rather than splitting on the basis of observations, we split the data set into training and test sets on the basis of sources. We use spectra corresponding to 34 sources for the training and the testing is performed on the remaining 27 sources.

(iii) Leave-one source out: In this method, we train the RF model on all observations corresponding to all sources except one. The observations corresponding to the excluded source are used for the testing.

Detailed description of each of these approaches is provided in the following sections.

4.1 Method 1: traditional train–test split

The orthodox way to perform any ML classification experiment is to divide the complete data set into train and test sets. For this, we used the `train_test_split` function of the `scikit-learn` (Pedregosa et al. 2011) PYTHON library. We keep 90 per cent of the data (13 396 observations) for the training and validation. The remaining 10 per cent of the data (1500 observations) are used for the testing. We train the RF algorithm with the best combination of parameters described in Section 3.0.1. Testing the trained RF model results in an overall accuracy of ~ 91 per cent. Table 1 shows the

**Figure 4.** Distribution of the data for the source-wise train–test split method. Both the train and test data sets have a good ratio of data for the two classes.

performance of the classifier for observations of both classes. The performance is equally good for the two classes.

The major drawback with the traditional train–test split method for our case is that it does not take into account potential correlations between different spectra of a given source. As a result, some observations from the same source might be used in both the training and test sets. Testing the classifier on different observations of a source that also had some of its data in the training set could lead to a biased and overestimated value of the accuracy as the classifier would be able to identify spectra belonging to the same source very easily. However, in the real-life scenario we would have data from a newly discovered X-ray source that needs to be classified. Since it is not possible to determine the expected accuracy for the real-life scenario with this method, we only use it for comparing the performance of different algorithms and choosing the best among them (Section 3).

4.2 Method 2: source-wise train–test split

To avoid the shortcomings of the traditional observation-wise train–test split, we split our data source wise; i.e. we select some sources to be used for training, while testing on the remaining sources. In order to maximize the usage of data available for training, we choose all the sources with less than 100 observations as the test sources while the remaining are used for training. With this criterion, we had a training set of 34 sources with a total of 13 601 observations (~ 90 per cent of the data) and a test set of 27 sources with a total of 1284 observations (~ 10 per cent of the data). The training set consists of 7950 BH LMXB observations from 21 sources (58 per cent) and 5651 NS LMXB observations from 13 sources (41 per cent). The test set consists of 719 BH LMXB observations from 15 sources (56 per cent) and 565 NS LMXB observations from 12 sources (44 per cent). These details are also represented in a graphical form in Fig. 4.

As can be observed from the figure, a satisfactory ratio between BH and NS observations is maintained in the train and test sets. The complete list of 27 sources used in the test set, actual class of each source from the literature, and total number of observations for each source are listed in Table A1. For each source, we provide all observations corresponding to that source to the classifier and each observation is assigned to ‘BH’ or ‘NS’ class. The percentage accuracy is computed by dividing the number of observations assigned to the actual class by the total number of observations

for that source. We provide the percentage accuracy for each source in the test set in the last column of the table.

The results obtained with this approach are also presented in Fig. 5 where most of the sources have above 60 per cent accuracy and only two sources have less than 50 per cent accuracy. For a quantitative analysis of the algorithm's performance, we calculate the sigma-clipped average source-wise accuracy using `sigma_clipped_stats` function of the astropy PYTHON library (Astropy Collaboration 2013). The sigma-clipped average accuracy gives an outlier resistant estimate of the algorithm's performance where the points lying beyond 3σ from the mean value are iteratively removed while computing the statistic. Sigma-clipped mean percentage accuracy for the test set comes out to be 88 per cent with a standard deviation of 12 per cent. Further class-wise performance is detailed in Table 2.

4.3 Method 3: leave-one source out

The source-wise train–test split method discussed in Section 4.2 closely mirrors the scenario we may have in terms of the available number of observations for a new source (which is not likely to exceed 100). However, the major drawback with the source-wise train–test split approach is that the test set remains unutilized for the training of the model. Although the test set contains only ~ 10 per cent of the observations, these observations might occupy a region in the model space crucial for identifying the classification boundary (the boundary in the model space that separates the data of the two classes) that might not be represented by the observations in the training set. Therefore, in order to optimize the usage of available data, we use the leave-one source out method, where we keep all observations from one source as our test data while using all the remaining sources for training. We repeat this experiment for each source, so that we have the results for all the observations from each of the 61 sources.

In the leave-one-source-out method, the sizes of the training and test sets vary in each run. Our final model would be trained on the entire data set whereas in this method, each model is using one source less than what the final model would use. Therefore, the coverage of the model in the feature space through this approach is closest to the final model. This can also be seen as a type of cross-validation method tailored for our data. We present the resulting accuracy for each source calculated through this method in Table A2 and Fig. 6.

There are four sources that lie below the 50 per cent average accuracy mark. The sigma-clipped average accuracy using this method comes out to be 87 ± 13 per cent, which gives a lower bound proxy on the performance of our final model. We present the class-wise performance in Table 3.

5 RESULTS AND INTERPRETATION

The average accuracies of the sources for both method 2 and method 3 are similar but less than that of method 1 (91 per cent). This is expected because of the bias in method 1 discussed earlier in Section 4.1. While the average accuracy decreases for methods 2 and 3 when compared to method 1, it is safe to say that the ML algorithm seems to do a satisfactory job in the overall classification of LMXB sources. The lower bound of the accuracy (87 ± 13 per cent) indicates that the RF algorithm is able to identify the classification boundary between the two types of X-ray sources in the 43-dimensional space of their energy spectra. However, we note that there are a few sources for which the accuracy is very low and

most of the observations of those sources are misclassified. In particular, there are four sources, namely XTE J1118+480 (BH), XTE J1748–288 (BH), IGR J00291+5934 (NS), and 1A 1246–588 (NS), which have less than 50 per cent accuracy out of which the observations of XTE J1118+480 and XTE J1748–288 are consistently misclassified with an overall accuracy percentage of ~ 10 per cent and ~ 30 per cent, respectively, in methods 2 and 3. This motivates us to study these sources in more detail and probe the possible reasons for the misclassification of their spectra. It is difficult to determine the reasons for the misclassifications directly from the RF algorithm. Therefore, we study the correlations between predictions of the RF algorithm and the factors that can influence them. Two such factors that can influence the energy spectra are the signal-to-noise ratio (SNR) and the physical states of LMXB systems.

5.1 Effect of SNR

For each observation, SNR is calculated by dividing the net count rate by the error in the net count rate. This information is obtained from the header of the spectra.pha file of the observations retrieved from the *RXTE* archive for each source. The SNR ranges from as low as 4 to more than 5800. To investigate the influence of SNR on the classification, we divide all observations into three SNR ranges, namely <100 , $100\text{--}1000$, and >1000 , and analyse the predicted probability of classification using method 3 (Section 4.3). The predicted probabilities are obtained using the `predict_proba` function of the RF model and serve as a measure of classification confidence. The distribution of predicted probabilities of correct identification for all observations in different SNR ranges is shown in Fig. 7. For observations with SNR <100 , the distribution of predicted probabilities peaks at 0.58. For the other two SNR ranges, namely $100\text{--}1000$ and >1000 , the distribution peaks at 0.87 and 0.91, respectively. These results are also presented in Table 4. This analysis indicates that the performance of the classification model increases with the increase in SNR.

We further investigated the misclassified sources by checking their average SNR. Among all the sources, only 1A 1246–588 had an average SNR less than 100 (avg. SNR = 48). This analysis indicates that, while the accuracy of the prediction increases in general with increasing SNR, a low SNR alone is the main reason behind the poor classification of the spectra for some sources.

5.2 Correlation between predicted probability of correct identifications and state transitions

In Fig. 8(a), we plot the CCD diagrams of two atoll-NS LMXBs (top panel) and HID diagrams of two BH LMXBs (bottom panel). The two atoll-NS sources are 4U 1728–34 (423 observations) and 4U 1636–53 (1563 observations) and the two BH sources are H 1743–32 (558 observations) and GRO J1655–40 (546 observations). We chose these systems as they have observations sampling all the typical spectral states.

We colour each observation based on the predicted probability of correct identification obtained from method 3 (leave-one source out) as shown in the colour bar plotted on the right side. Most of the misclassified observations (darker coloured circles) belong to the LHS or intermediate states while the HSS observations are very well classified (lighter coloured points).

In Fig. 8(b), we show the HID and CCD diagrams for the four sources for which our algorithm performs the worst. While the

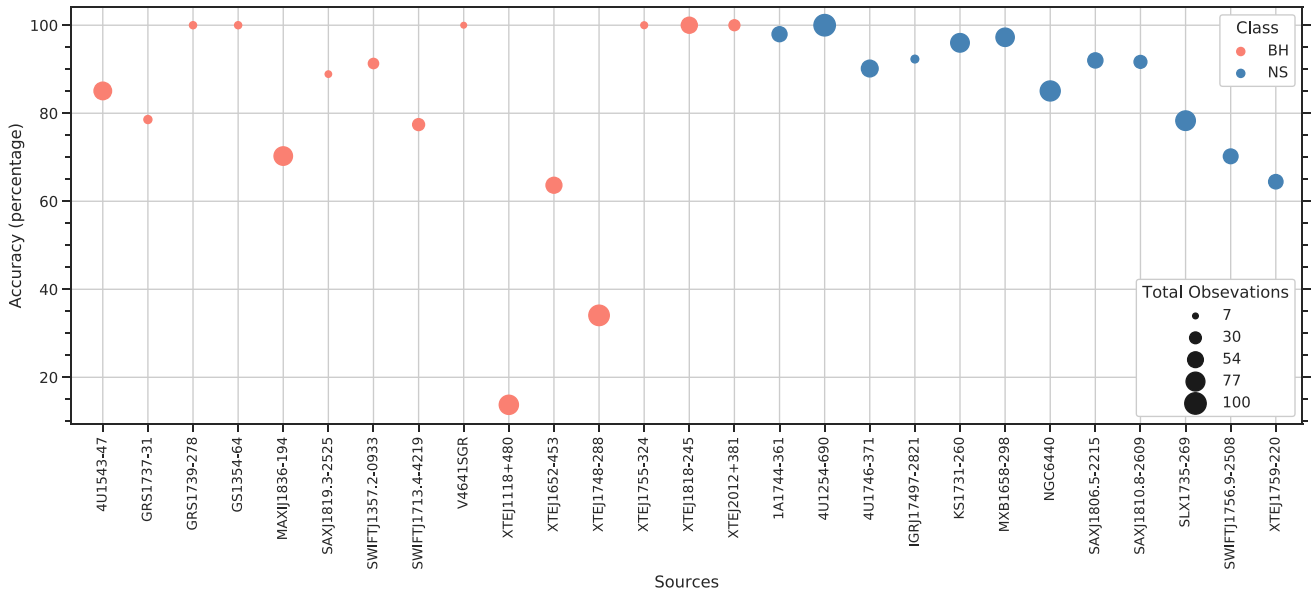


Figure 5. Plot showing individual source-wise accuracies for sources in the test set of the source-wise train–test split method. The points are coloured based on the classes and the size of the points corresponds to the number of observations in each source.

Table 2. Performance of the RF classification model for NS–BH classification using the source-wise train–test split method.

Class	No. of sources	Avg. per cent accuracy	σ
NS	12	88	11
BH	15	80	25
Total	27	88	12

state transitions for these sources are not as pronounced as for the sources shown in Fig. 8(a), we can still observe that the misclassifications (dark points) are predominantly in the hard region of the spectra.

In Fig. 9, we further investigate the correlation between hard colour and predicted probability of correct identification of NS and BH LMXB observations for the different SNR ranges mentioned in Section 5.1. It follows the results shown in Figs 7 and 8. For the case of NS LMXBs, we find that most of the observations in the low-SNR range have predicted probability peaking around 0.5 and hard colour value of 1.0. In the case of low-SNR observations in BH LMXBs, the predicted probabilities of most observations decrease as we increase the hard colour value and then increase back again at hard colour values >2 . The same trend follows for BH LMXBs with SNR between 100 and 1000 although most observations this time have low hard colour values and higher predicted probabilities. For BH LMXBs with SNR >1000 , most observations have low hard colour values and high predicted probabilities. In the case of the higher SNR ranges (>100) for NS LMXBs, most observations have predicted probability around 1.0 and hard colour values <1.0 . These plots again indicate that the algorithm can classify observations with low hard colour values, i.e. observations in the HSS, the best and the prediction accuracy increases with SNR.

5.3 Prediction for sample sources with unknown classification

We use the final RF model trained on all 61 sources to predict the classification of a sample of 13 systems where the nature of the compact object is still unknown or under debate. These 13 sources were sampled with a total of 766 *RXTE/PCA* observations. Our results and predictions are summarized in table 5.

If >50 per cent of the observations of a source were predicted to belong to a particular class, that class was assigned to the source. Among the 13 sources, 5 sources (XTE J1901+014, XTE J1719–291, XTE J1727–476, IGR J17285–2922, and XTE J1856+053) have very few observations (<10) that meet our criteria for good data (i.e. net count rate >5 counts per second) and thus it is difficult for us to make any comments on the predicted classes for these sources. The remaining 8 sources (4U 1822–371, 4U 1957+11, IGR J17494–3030, SAX J1711.6–3808, SLX 1746–331, Swift J1842.5–1124, XTE J1637–498, and XTE J1752–223) all have more than 30 observations each. Based on our criteria for classification mentioned earlier, six sources (4U 1822–371, 4U 1957+11, SLX 1746–331, Swift J1842.5–1124, XTE J1637–498, and XTE J1752–223) were classified as BH LMXBs while two sources (IGR J17494–3030 and SAX J1711.6–3808) were classified as NS LMXBs.

Among the 8 sources with >30 observations, 5 sources have prediction percentage >60 per cent. Our model predicts that the source SAX J1711.6–3808 is a NS LMXB for 94 per cent of its observations; however, Sánchez-Fernández et al. (2006) claim that SAX J1711.6–3808 might contain a BH with a high-spin parameter based on their fit of the X-ray spectra. For 88 per cent of its observations, the source SLX 1746–331 is predicted to have a BH, as speculated by White & Van Paradijs (1996) in their paper. Multiple works have argued that the compact object in 4U 1957+11 is a BH (Nowak et al. 2011; Gomez, Mason & Robinson 2015) and our algorithm predicts the same for 72 per cent of its 121 observations. XTE J1752–223 is considered a BH LMXB candidate by Shaposhnikov et al. (2010) in their paper and our algorithm classified 67 per cent of its observations as a BH LMXB. The nature

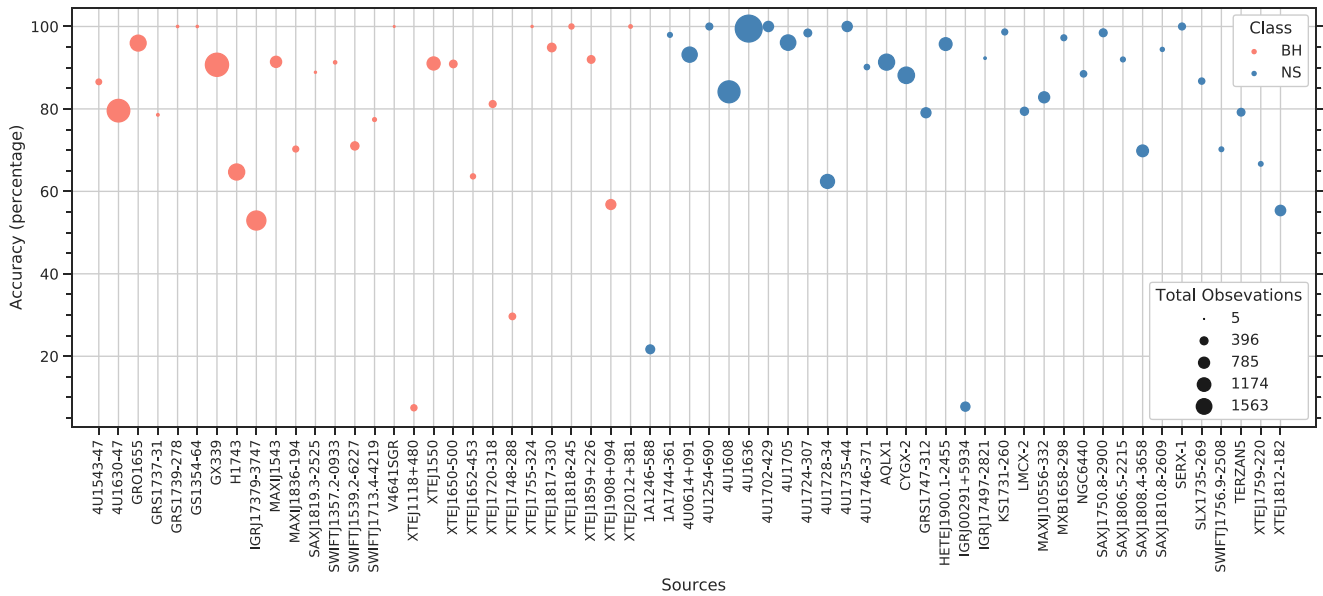


Figure 6. Plot showing individual source-wise accuracies using the leave-one source out method of cross-validation. The points are coloured based on the classes and the area of the points corresponds to the number of observations in each source.

Table 3. Performance of the RF classifier for NS–BH classification using the leave-one source out method. Average accuracies and standard deviations are computed using 3σ clipping to get a robust estimate of the statistics.

Class	No. of sources	Avg. accuracy	σ
NS	33	89	11
BH	28	85	14
Combined	61	86.63	13.08

Table 4. Predicted probability and distribution of observations for different ranges of SNR.

SNR range	Mode of predicted probabilities	Total obs.	Data (per cent)
<100	0.58	2706	18.2
100–1000	0.87	10 348	69.5
>1000	0.91	1831	12.3

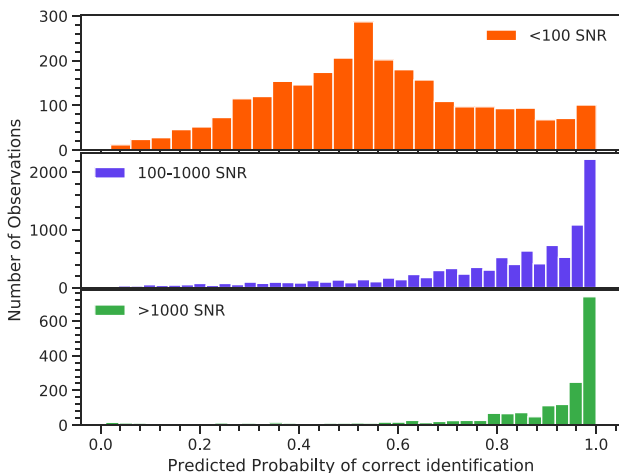


Figure 7. Distribution of predicted probabilities (confidence) for different SNR ranges. The distributions peak at 0.58, 0.87, and 0.91 (top to bottom), indicating that observations with higher SNR are correctly classified with a greater confidence.

of the compact object in XTE J1637–498 is uncertain, but Tetarenko et al. (2016) consider it as a BH in their data base. 66 per cent of the observations of XTE J1637–498 are classified as BH LMXB by our algorithm.

For the remaining three sources out of the aforementioned eight, the prediction percentage is <60 per cent, but still >50 per cent. For these sources, we consider that the algorithm is confused about the nature of the compact object in the LMXBs. The source 4U 1822–371 is predicted to be a BH LMXB for 55 per cent of its observations but Jonker & van der Klis (2001) detected pulsations from this source indicating that it most certainly is a NS LMXB. Armas Padilla, Wijnands & Degenaar (2013) have suggested that the source IGR J17494–3030 might be a NS LMXB and our trained model also predicts the same for 54 per cent of its 97 observations. Swift J1842.5–1124 was classified by Zhao et al. (2016) as a BH LMXB candidate and our trained model predicts that it is a BH for 51 per cent of its observations. Apart from that, it is also important to note that all the 13 sources in our prediction sample have an average SNR <100, which is the region where the algorithm has the worst performance as shown in Fig. 7.

6 SUMMARY AND DISCUSSION

We used archival data from the PCA instrument aboard the *RXTE* mission (now decommissioned) to train an RF algorithm that we

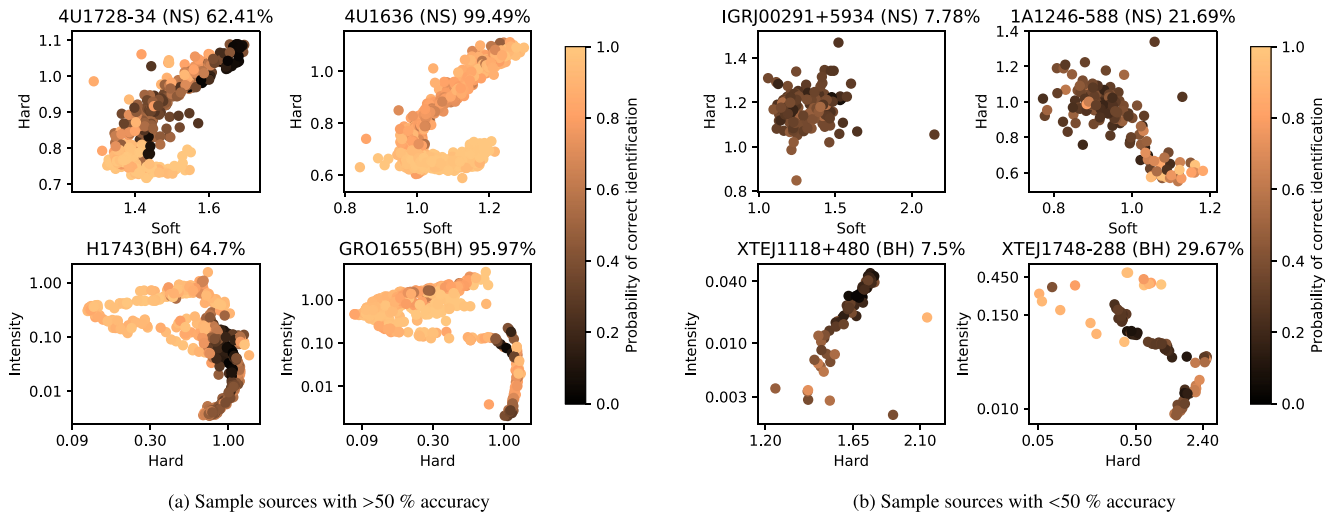


Figure 8. CCDs and HIDs for NS and BH LMXB systems, respectively. Left-hand panel shows the CCDs and HIDs for two NS (top) and two BH (bottom) sources with good classification accuracy. Right-hand panels show the same diagrams for poorly classified NS and BH systems using the RF classifier. Probability of correct identification for each observation using method 3 is colour coded as shown in the adjacent colour bars. The source identifiers and their original classes are indicated on top of each diagram with their accuracy percentage from Table A2.

subsequently use to classify a group of LMXB systems into BH or NS LMXB just by using their energy spectra as input. The data consist of 43 count rate values corresponding to the energy range of 5–25 keV for each observation of a source. The data set consists of 14 885 observations from 61 individual sources: 6216 observations from 28 BH systems and 8669 observations corresponding to 33 NS systems. We perform the training and testing using three different methods for a robust assessment of the performance of the RF algorithm for NS–BH classification. We obtain the outlier-resistant average model accuracy of 87 ± 13 per cent at 1σ confidence level in classifying these systems. The final trained model is used to predict the classes of X-ray sources of unknown nature.

We also analyse the results of the classification by looking at the effect that SNR and state transitions have on the predicted probabilities of correct identification. As expected, it is observed that with better SNR the mean predicted probability of correct identification for observations increases. It is also observed that most of the observations (especially in the high SNR ranges) with a higher predicted probability have low hard colour values and lie in the HSS. The higher predicted probability values of observations in the HSS can be attributed to their high SNR values. Another possible explanation to justify the better classification of observations in the HSS is the presence of a NS surface in the spectra of the HSS, which would be absent in the HSS spectra of BH LMXBs.

To further investigate this, in Fig. 10 we plot the feature importance for the input spectra. The feature importance represents the relative importance that the ML algorithm gives to the given input data (in this case, flux at a given energy bin). Fig. 10 shows that both the lower end and higher end of the spectra appear to be the most important parts of the energy spectra in order to differentiate between BH and NS. The least important part of the spectrum is around 18–19 keV, and around 12 keV there is a small bump suggesting that there might be weak features at this energy that also play an important role in the classification. The fact that Fig. 10 does not show a flat distribution is important, as it indicates that the algorithm is taking into account underlying differences in the energy spectra, which probably relate

to subtle intrinsic physical differences between BH and NS (e.g. the presence of a surface and a boundary layer in the NS, potential differences in the size of the corona, contribution of the jet to the X-rays, etc.).

This, in turn, is pivotal to argue that if future works can use more interpretable class of algorithms (see for e.g. Villaescusa-Navarro et al. 2020; Udrescu & Tegmark 2020, and references therein) for this type of classification, then there is potential to use ML techniques to learn more about the differences between BHs and NSs from their spectral characteristics.

The main objective of this work was to probe whether ML techniques can be employed to determine the class of a newly observed LMXB source just by using the information contained in its energy spectra. Our results show that despite below average performance for a few sources, the RF algorithm does a reasonably good job in classifying the NS–BH LMXBs overall. The most important aspect of this method is the speed of the classifications. Given an energy spectrum of an LMXB source, the algorithm is able to assign a class label to it in a fraction of a second. The algorithm also gives a probability of the predicted class for the spectrum that can be used as a confidence measure for the prediction. This algorithm has the potential of being used as a tool to very quickly flag the spectra of a newly identified source that can be helpful for scheduling follow-ups on particular objects of interest. It is also important to note that in most cases the net confidence of the predictions increases for a source as we add more observations.

One issue that we face currently in our work is that our classification model cannot be used directly to classify the energy spectra from other X-ray missions. The main reason for this is that most of the other currently active X-ray missions have instruments with effective areas that are different to *RXTE*'s PCA. The first idea towards tackling this issue is to train a classification model for each instrument using their data. The problem that may arise while trying to do this is that there may not be enough data to train an ML algorithm for each instrument, which was one of the main reasons why we chose to work with data from *RXTE* even though it is now decommissioned. However, the concept of transfer learning could be employed to train

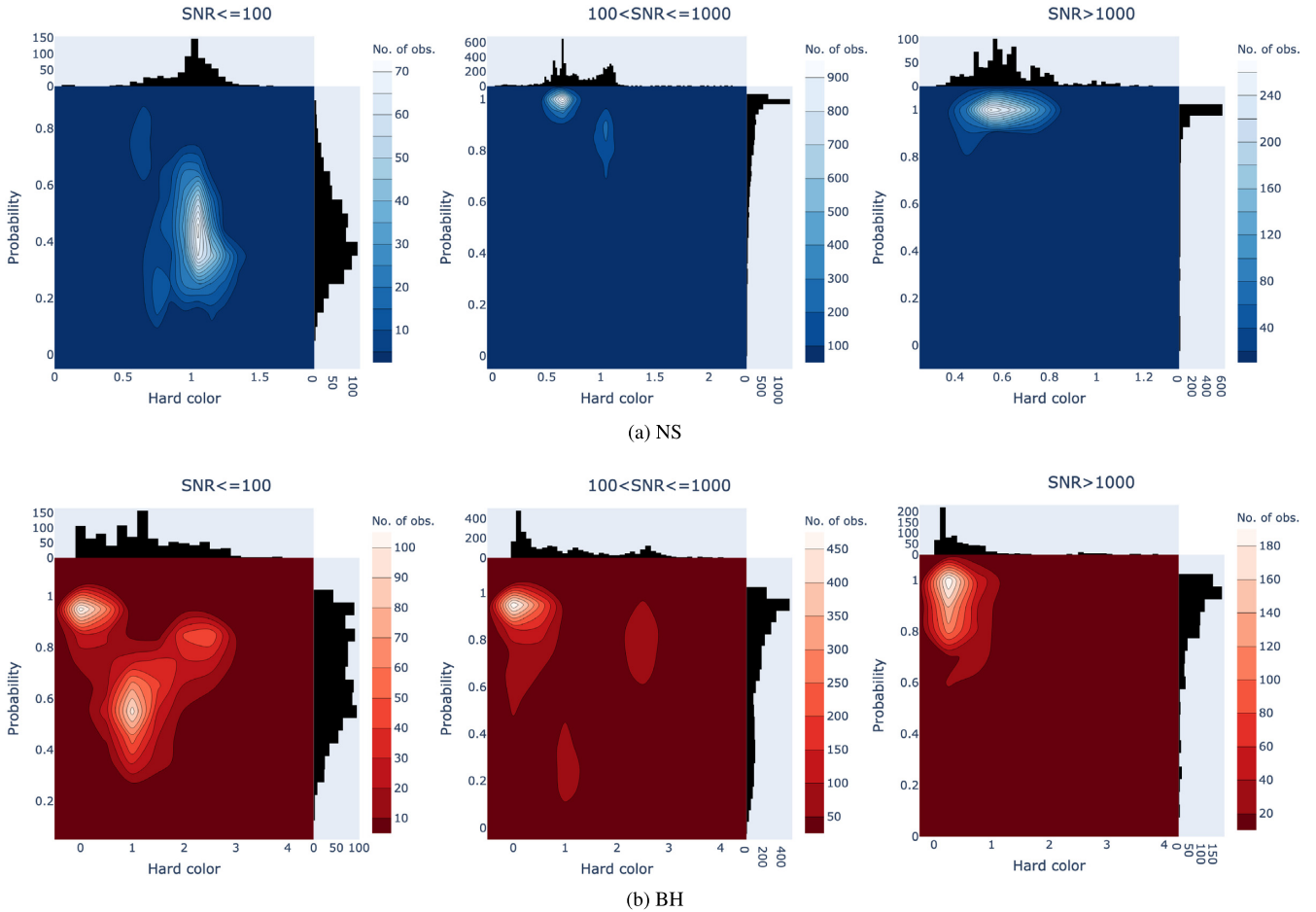


Figure 9. Bivariate density plots of hard colour and predicted probability of correct identification for NS and BH LMXB observations in different SNR ranges. The colour bar shows the number of observations in each region. We have 1518, 3650, and 813 observations in the SNR less than 100, between 100 and 1000, and greater than 1000 ranges, respectively, for BH LMXBs. Similarly, for NS LMXBs we have 1188, 6698, and 1018 observations in the SNR less than 100, between 100 and 1000, and greater than 1000 ranges, respectively. The light-coloured regions of the plots have the most number of observations. The individual univariate histogram plots for hard colour and predicted probability are also shown on their respective axes. As can be observed, all the plots indicate that it is easier to classify observations with low hard colour values and high SNR values.

Table 5. Classification results for sources in the prediction set. A class was assigned to a source if the majority of its observations were predicted to belong to that class. In cases where the ratio was 50–50 (XTE J1719-291), it is indicated that the source can belong to either class.

Source name	Total obs.	Class (predicted)	Prediction (per cent)	Avg. SNR
4U 1822–371	97	BH	55.67	67
4U 1957+11	121	BH	72.73	22.38
IGR J17285–2922	5	BH	60	10.03
IGR J17494–3030	97	NS	54.64	25.84
SAX J1711.6–3808	34	NS	94.12	34.35
SLX 1746–331	65	BH	87.69	26.82
Swift J1842.5–1124	49	BH	51.02	25.71
XTE J1637–498	76	BH	65.79	8.41
XTE J1719–291	2	NS/BH	50	2.82
XTE J1727–476	4	BH	100	6.3
XTE J1752–223	210	BH	67.14	56
XTE J1856+053	5	BH	100	10.75
XTE J1901+014	1	BH	100	1.1

an algorithm for another instrument with limited data using our pre-trained classification model for the *RXTE* data. More details on the idea behind transfer learning can be found in Pan & Yang (2009).

Another alternative approach could be to use some sort of transformation to convert the data from a different instrument into the *RXTE*/PCA format. The transformed data can then be directly plugged into the pre-trained model. It is important, however, to realize that such a transformation is only possible for data obtained from instruments that have overlapping operational energy range (i.e. at least 5–25 keV). This rules out data obtained from instruments that operate specifically at lower energy ranges (e.g. the *Swift*'s X-Ray Telescope) as we do not use data below 5 keV to avoid any effect of interstellar absorption.

Adding more information as input to the algorithm can also be explored as a means of improving the current level of accuracy reached for all the sources in our data set. One way of doing that would be to combine the energy spectra with the power spectra of all observations for each source. There are many more potential directions that can be explored in the future for solving the problem of LMXB spectral classification. We believe that our experiment can serve as a starting point for the application of ML

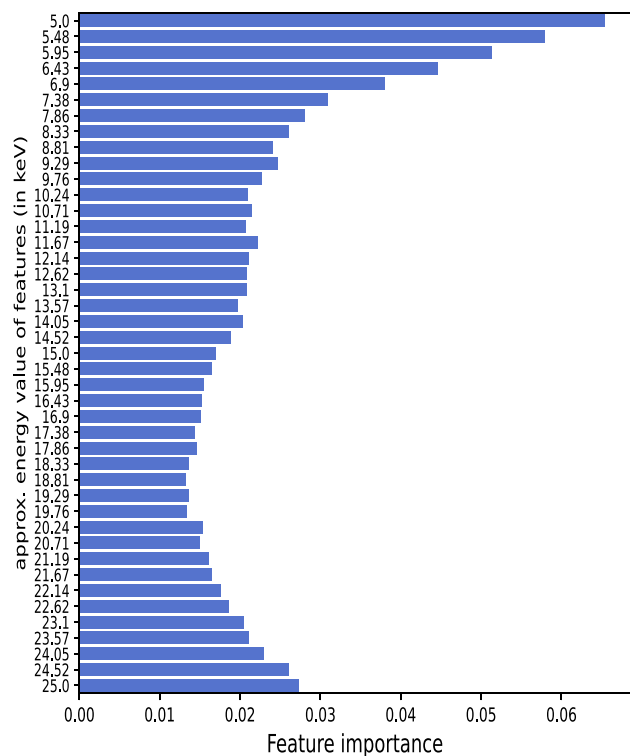


Figure 10. Feature importance plot for the input features. The y-axis shows approximate energy values corresponding to each element in the input to the algorithm. The energy values increase from top to bottom. The x-axis has the feature importance of each element in the input vector to the algorithm. The sum of all importance values is equal to 1.

methods to solve this and other problems in the domain of X-ray astronomy.

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DATA AVAILABILITY

The data underlying this article are publicly available in the High Energy Astrophysics Science Archive Research Center (HEASARC) at <https://heasarc.gsfc.nasa.gov/db-perl/W3Browse/w3browse.pl>.

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APPENDIX A: COMPLETE TABLES OF SOURCE-WISE ACCURACIES FOR METHOD 2 AND METHOD 3

Table A1. Source-wise performance of algorithm in method 2 (source-wise train–test split).

Source names	Class	Total test obs.	Correctly classified	Misclassified	Accuracy percentage
XTE J1118+480	BH	80	11	69	13.75
XTE J1748–288	BH	91	31	60	34.07
XTE J1652–453	BH	55	35	20	63.64
XTE J1759–220	NS	45	29	16	64.44
Swift J1756.9–2508	NS	47	33	14	70.21
MAXI J1836–194	BH	74	52	22	70.27
Swift J1713.4–4219	BH	31	24	7	77.42
SLX 1735–269	NS	83	65	18	78.31
GRS 1737–31	BH	14	11	3	78.57
NGC 6440	NS	87	74	13	85.06
4U 1543–47	BH	67	57	10	85.07
SAX J1819.3–2525	BH	9	8	1	88.89
4U 1746–371	NS	61	55	6	90.16
Swift J1357.2–0933	BH	23	21	2	91.3
SAX J1810.8–2609	NS	36	33	3	91.67
SAX J1806.5–2215	NS	50	46	4	92
IGR J17497–2821	NS	13	12	1	92.31
KS 1731–260	NS	75	72	3	96
MXB 1658–298	NS	73	71	2	97.26
1A 1744–361	NS	49	48	1	97.96
XTE J1755–324	BH	10	10	0	100
XTE J2012+381	BH	26	26	0	100
4U 1254–690	NS	100	100	0	100
GS 1354–64	BH	11	11	0	100
GRS 1739–278	BH	11	11	0	100
V4641 SGR	BH	7	7	0	100
XTE J1818–245	BH	56	56	0	100

Table A2. Source-wise performance of algorithm in method 3 (leave-one source out).

Source names	Class	Total test obs.	Correctly classified	Misclassified	Accuracy percentage
XTE J1118+480	BH	80	6	74	7.5
IGR J00291+5934	NS	180	14	166	7.78
1A 1246–588	NS	166	36	130	21.69
XTE J1748–288	BH	91	27	64	29.67
IGR J17379–3747	BH	784	415	369	52.93
XTE J1812–182	NS	233	129	104	55.36
XTE J1908+094	BH	213	121	92	56.81
4U 1728–34	NS	423	264	159	62.41
XTE J1652–453	BH	55	35	20	63.64
H1743–32	BH	558	361	197	64.7
XTE J1759–220	NS	45	30	15	66.67
SAX J1808.4–3658	NS	295	206	89	69.83
Swift J1756.9–2508	NS	47	33	14	70.21
MAXI J1836–194	BH	74	52	22	70.27
Swift J1539.2–6227	BH	145	103	42	71.03
Swift J1713.4–4219	BH	31	24	7	77.42
GRS 1737–31	BH	14	11	3	78.57
GRS 1747–312	NS	215	170	45	79.07
TERZAN5	NS	125	99	26	79.2
LMC X–2	NS	141	112	29	79.43
4U 1630–47	BH	1102	877	225	79.58
XTE J1720–318	BH	101	82	19	81.19
MAXI J10556–332	NS	262	217	45	82.82
4U 1608–52	NS	1041	876	165	84.15
4U 1543–47	BH	67	58	9	86.57
SLX 1735–269	NS	83	72	11	86.75
CYG X–2	NS	583	514	69	88.16
NGC 6440	NS	87	77	10	88.51
SAX J1819.3–2525	BH	9	8	1	88.89
4U 1746–371	NS	61	55	6	90.16
GX 339–4	BH	1163	1055	108	90.71
XTE J1650–500	BH	121	110	11	90.91
XTE J1550–564	BH	368	335	33	91.03
Swift J1357.2–0933	BH	23	21	2	91.3
AQL X1	NS	555	507	48	91.35
MAXI J1543–564	BH	268	245	23	91.42
SAX J1806.5–2215	NS	50	46	4	92
XTE J1859+226	BH	125	115	10	92
IGR J17497–2821	NS	13	12	1	92.31
4U 0614+091	NS	498	464	34	93.17
SAX J1810.8–2609	NS	36	34	2	94.44
XTE J1817–330	BH	157	149	8	94.9
HETE J1900.1–2455	NS	351	336	15	95.73
GRO J1655–40	BH	546	524	22	95.97
4U 1705–44	NS	512	492	20	96.09
MXB 1658–298	NS	73	71	2	97.26
1A 1744–361	NS	49	48	1	97.96
4U 1724–307	NS	127	125	2	98.43
SAX J1750.8–2900	NS	131	129	2	98.47
KS 1731–260	NS	75	74	1	98.67
4U 1636–53	NS	1563	1555	8	99.49
4U 1254–690	NS	100	100	0	100
V4641 SGR	BH	7	7	0	100
XTE J1755–324	BH	10	10	0	100
XTE J2012+381	BH	26	26	0	100
GS 1354–64	BH	11	11	0	100
XTE J1818–245	BH	56	56	0	100
SERX–1	NS	102	102	0	100
4U 1702–429	NS	225	225	0	100
GRS 1739–278	BH	11	11	0	100
4U 1735–44	NS	222	222	0	100