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Advances in Pulsar Candidate Selection: A Neural Network Perspective

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Abstract

Pulsars have played an important role in comprehending the universe. They play a key role in understanding various phenomena like general relativity, gravitational waves, properties of matter, collision of black holes and the evolution of stars and nebulae. Thus, identifying them is a crucial task. The increasing number of surveys has created a large volume of candidate samples, in the range of several million. Hence, it is impossible to select pulsars from these samples using human-driven methods. Automatic Pulsar Candidate Identification (APCI) was introduced for this purpose. In recent years, various deep-learning techniques and models have been implemented for this purpose. Specific deep neural network models and hybrid models were designed to select pulsar candidates from various surveys consisting of radio and X-ray samples. In this study, a series of models implementing ANN, CNN and GNN are discussed capable of selecting pulsar candidates. These models were trained using a wide range of surveys.

Keywords: Pulsars, Neural Networks, Candidate Selection, Deep Learning

1. Introduction

Pulsars are neutron stars that emit electromagnetic radiation in a periodic pattern. They were first discovered in 1967 by Bell and Hewish [1]. Since their discovery, pulsars have played a pivotal role in understanding nuclear physics, stellar evolution and the behavior and properties of matter under extreme conditions. They can also be used to study dark matter and dark energy as well as the evolution of binary and multiple star systems [14]. Researchers are

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paying more attention to the pulsars because of their impact on astrophysics and astronomy. These highly magnetized rotating stars provided the first evidence of gravitational waves [2].

More than 3000 pulsars have been discovered using various selection techniques. The majority of pulsars have been discovered using modern surveys including the Parkers Multi-Beam Survey (PMPS) [3], Pulsar Arecibo L-band Feed Array (PALFA) survey [4], High Time Resolution Universe (HTRU) survey [5], Green Bank Telescope (GBT) drift-scan pulsar survey [6], Low-Frequency Array (LOFAR) survey [7] and the Commensal Radio Astronomy FAST Surveys (CRAFTS).

These surveys generate a large volume of datasets. For example, the GBT drift-scan survey generated about 1.2 million candidates [6]. These sets contain both pulsars and noise. The creation of pulsar candidates from these radio signals generally includes three steps, namely the elimination of RFI (Radio Frequency Interface), de-dispersion and the Fast Fourier Transform (FFT) [14]. In the traditional approach, a manual expert will review these candidates in 1-300 seconds. In this pattern, studying millions of candidates would take several thousand hours to scan millions of candidates. Hence, the development of an automatic, efficient and highly accurate approach to candidate selection is needed at the current time. For this purpose, several deep learning techniques (neural networks) have been introduced to efficiently select pulsar candidates from these surveys.

A critical phase in analysing radio astronomy data, especially when searching for new pulsars, is the selection of pulsar candidates. The characteristics listed below highlight how crucial deep learning techniques are to PCS (Pulsar Candidate Selection).

i. **Data Volume:** Radio telescopes produce vast amounts of data. Pulsar surveys can result in terabytes of data per observation session. Manual inspection of all this data is practically impossible and time-consuming.

ii. **Data-Driven Exploration:** Automated techniques can uncover unexpected patterns or phenomena that might lead to discoveries and insights.

iii. **Handling Complex Data:** Radio astronomy data can be affected by various sources of interference and noise. Automated methods can learn to distinguish between actual pulsar signals and artifacts.

iv. **Objective Selection:** Automated processes eliminate subjective biases and interpretations affecting manual candidate selection.

2. Pulsar Processing Pipeline

The pulsar identification process generally has two main stages [8]. Stage 1 includes pre-processing, de-dispersion, periodicity search and feature extraction [15]. Stage 2 analyses the processing output to select good pulsar candidates [8]. Various deep-learning techniques are applied to select pulsar candidates in this stage effectively. The figure 1 shows the flow diagram of a typical pulsar processing pipeline.

1. **Pre-Processing:** The first step is identifying RFI from the acquired data. For this purpose, the data is divided into blocks of time and frequency. Each block is analysed, and if an RFI is found, then the sample is flagged or replaced. However, due to its complex nature, complete RFI removal is yet to be achieved here.

2. **De-Dispersion:** While travelling through the interstellar medium, radio signals experience dispersion, which causes the lower frequencies to arrive later than higher frequencies. This delay is compensated by adjusting time delays associated with different frequencies.

3. **Periodicity Search:** The next step involves searching for regular patterns that could correspond to pulsar signals. For this purpose, the Fast Fourier Transform (FFT) is widely used.

4. **Pulse Profile Analysis:** A more detailed analysis of their pulse profiles is conducted after identifying potential periodic signals. Pulse profiles provide insights into the pulse shape and intensity variations over time. This analysis aids in distinguishing genuine pulsar signals from noise or interference.

5. **Multi-Criteria Analysis/ Feature Extraction:** Pulsar candidate selection often involves multiple criteria beyond periodicity, such as dispersion measure (DM), signal-to-noise ratio (S/N), and pulse width. These criteria are collectively considered to filter out false positives and prioritize potential candidates.

6. **Feature Extraction:** Diagnostic plots and additional statistical characteristics are calculated here. The diagnostic plots contain a small set of features, including S/N ratio,

DM, period, pulse width, integrated pulse profile, and two-dimensional (2D) plots displaying the signals' variance concerning time, frequency, and DM [13].

7. **Machine Learning Classification:** Machine learning algorithms have gained prominence in candidate selection in recent years. These algorithms are trained on labelled data to distinguish between accurate pulsar signals and various forms of noise. Their ability to recognise complex patterns can improve the selection process.

8. **Post-Selection Verification:** Selected candidates undergo further scrutiny, including follow-up observations with multiple telescopes and wavelengths. This verification process confirms the candidates' authenticity and eliminates any remaining false positives.

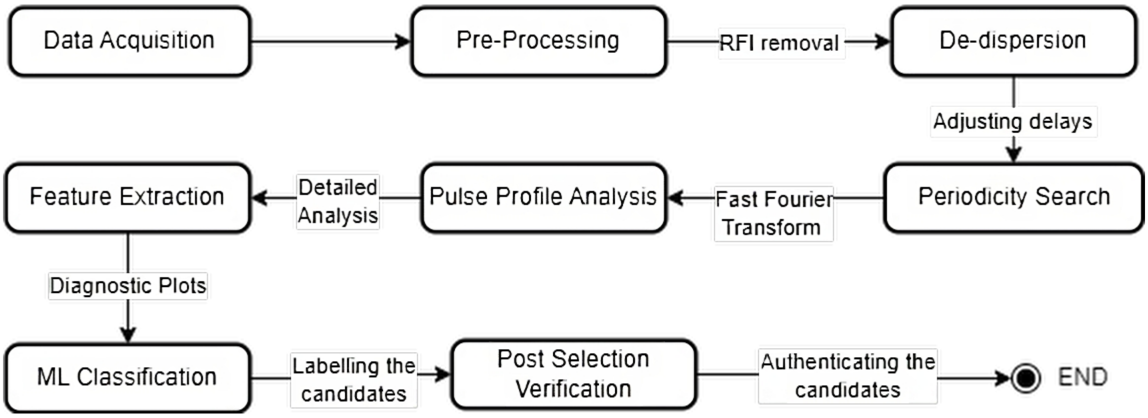

Figure 1. The Flow Diagram of a Pulsar Processing Pipeline

3. Implementing Neural Networks in Pulsar Selection

Automated classification techniques have proved to be quite useful for faster and more efficient pulsar candidate selection. Traditional approaches include manual selection, selection using graphical tools or applying scoring (or ranking) techniques. These traditional methods were time-consuming and highly inefficient. Hence various machine learning algorithms have been implemented in this domain. The ability of neural networks to identify complex features and patterns made them a more promising choice for the automated selection process. The neural networks proved to be highly time efficient and have shown greater accuracy in classification than the traditional methods.

3.1 ANN-based Pulsar Selection Methods

ANN was implemented for the first time for pulsar selection in 2010 [8]. An 8:2:2 architecture followed by a 12:12:2 architecture was used to identify pulsar stars from the PMPS. A pulsar named PSR J1926+0739 was successfully detected using the 8:2:2 model. The ANNs were developed for candidate selection from a dataset of around 16 million candidates of the PMPS. The selection statistics of the 8:2:2 model showed that 1 in every 30 selected candidates is a pulsar. However, the model did not achieve the expected accuracy because of an imbalanced dataset and abnormal candidate plots.

An ANN was constructed to have output that ‘scores’to represent the similarity of an object to a pulsar from different properties like flux, sky position, and spectral index [9]. This ‘score’ indicates the likeness of a candidate to be a pulsar. The ANN was developed using radio sources cross-matched between TGSS (TIFR GMRT Sky Survey) and NVSS (NRAO VLA Sky Survey).

The input parameters were divided into seven main categories: galactic latitude and longitude, absolute galactic latitude, TGSS flux, NVSS flux, spectral index and source compactness. Then four sets of these features were taken as input parameters and the same model was trained with these different sets. One hundred-seven pulsars and 10,000 non-pulsars were used to train the model. The model trained with the set containing galactic latitude and its absolute value, TGSS and NVSS flux and compactness showed the best accuracy with a precision of 98.8% and recall of 84.6%.

3.2 CNN-based Pulsar Selection Methods for Radio Astronomy

3.2.1 Using CNN

VGG-net, and a CNN architecture for pulsar classification is implemented [11] . The VGG network consists of a series of convolutional layers followed by max-pooling layers. A typical VGG-net model starts with convolutional layers with a 3×3 filter and a stride of 1, followed by a max-pooling layer with a stride of 2. This increases the depth of the network using smaller filters. The network consists of 5 max-pooling layers and three fully connected layers. The soft-max layer is used as the final output layer.

They used a dataset from the HTRU survey. The dataset contains 1196 pulsars and 89,995 non-pulsar candidates. The problem with HTRU is that it is very imbalanced. Hence, the oversampling method increased the number of positive samples (pulsars). Over-sampling helped in the practical training of the model. This model underwent 50 training iterations using a batch size of 512. Since VGG-net takes an image as input, an ANN model was developed to extract features from the input data. The extracted features were transformed into matrix-like images, allowing VGG-net to operate on data.

For evolving the model, a ten-fold cross-validation technique was used. Classification performance measured during cross-validation showed a precision of 0.91 and recall of 0.94 for the positive samples (pulsars). This showed that the VGG-net model was better at pulsar classification compared to contemporary machine learning algorithms like MLP (Multi-Layer Perceptron), NB (Naive Bayes), C4.5, GH-VFDT (Gini Heuristic - Very Fast Decision Tree), and SVM (Support Vector Machine). Table 1 shows a comparison of F1- score, precision and recall between CNN and contemporary ML algorithms. The results were obtained from fifty years of pulsar candidate selection [17].

Table 1. Comparison of VGG-Net with Contemporary ML Models

Model	F1 - Score	Precision	Recall
C4.5	0.74	0.63	0.90
MLP	0.75	0.65	0.91
NB	0.69	0.57	0.86
SVM	0.78	0.72	0.87
GH-VFDT	0.86	0.89	0.82
VGG-Net	0.92	0.91	0.94

The scores of CNN (VGG-Net) clearly shows that it out-performs all state-of-art traditional machine learning algorithms.

3.2.2 Using Deep CNN

Wang, Yuan-Chao et al [10] designed an 11-layer deep convolutional neural network for classifying pulsar candidates. The model consists of 8 convolutional layers, 1 flatten layer, and two fully connected layers. The HTRU-1 [16] dataset was used as input for the model. The dataset was randomly divided into three parts: 60% for training, 20% for validation, and 20% for testing.

Data augmentation methods were introduced to address the issue of class imbalance. The Synthetic Minority Over-sampling Technique (SMOTE) was introduced for this purpose. This resulted in the generation of new supplementary pulsar candidates for training purposes.

The input size was 64×64×2, containing sub-integration and sub-band plots. The model outputs a 1×2 tensor, which means a probability of a pulsar or a non-pulsar. The model trained with data augmentation showed a recall of 0.962 and a precision of 0.963. This showed that the model can extract features well and reliably classify pulsar candidates. However, the model is not generalized well for weaker pulsar signals, because the subplots of these candidates are not easy to identify.

3.3 CNN-based Pulsar Selection Methods for X-Ray Astronomy

The above-mentioned techniques were trained and developed for radio sources. [12] implemented CNN to select pulsar candidates from X-ray observations. Certain young pulsars showed emission in the X-ray range and almost no emission in the radio waves. Hence, the study was focused precisely on detection techniques for X-rays. X-rays have energetic particles which are not affected by interstellar dispersion. Hence, features like the S/N ratio and DM curve are ineffective for X-rays.

A GAN model was used for data augmentation during the pre-processing stage. Here, six new statistical parameters, including skewness, kurtosis, shape factor, information entropy, variance, and clearance, were extracted after applying the epoch folding (EF) technique. EF is generally used to enhance the pulsar signal and to reduce the noise effects. At last, a frequency-feature curve is generated by integrating above mentioned statistical features. These frequency-feature curves are converted into two-dimensional images and used as input for CNN.

A simulated training set created using non-homogeneous Poison process was used for training. The data from RXTE (Rossi X-ray Timing Explorer) was used to test the model. The results showed a recall and precision of 0.996 and 0.983, respectively. The experiment showed the highest recall and precision compared to contemporary radio frequency data models. This showed that the model was effective for candidate selection based on X-ray observations.

3.4 Generative Adversarial Network-based Selection Methods

For the purpose of APCI, CNN was highly preferred. However, due to the problem of class imbalance, it is challenging to enhance the performance of CNN. Also, a large number of training samples are required to train a deep CNN model fully. If the training dataset with class imbalance is used, then the most unseen sample can be falsely be recognized as a pulsar candidate.

To alleviate this issue, Guo et al [15] proposed a framework that combines a deep convolution generative adversarial network (DCGAN) with a support vector machine (SVM). The DCGAN+L2-SVM framework addresses the class imbalance problem more efficiently than CNN. DCGAN is a type of GAN which is capable of learning image feature representations in an unsupervised learning manner. The L2-SVM linear classifier is trained to predict labels of new input data.

Here, the authors use time-vs-phase and frequency-vs-phase two-dimensional plots as input for the framework. The samples used were HTRU-Medlat, which contains 1196 positive candidates and 89,996 negative candidates and PMPS-26k, which is an artificially identified dataset created from PMPS. The training of this hybrid framework showed better results than the existing CNN models.

The authors further performed a training comparison of DCGAN+L2-SVM with a CNN model for HTRU-Medlat and PMPS-26k. Their proposed framework outperforms CNN in both the inputs, time-vs-phase and frequency-vs-phase plots.

3.5 Residual Network-based Selection Methods

In deep networks, during back-propagation, the gradient either diminishes or grows exponentially as the it passes through multiple layers. This leads to the problem of gradient degradation during the model's training. To address this issue, a residual network or the ResNet was introduced. ResNet is a form of CNN designed specially to overcome gradient degradation. Also, the ResNet has a better ability to fit data than the CNN; hence, it can achieve feature extraction with more classification ability with a smaller dataset [14].

Wang, et al [13] developed a ResNet model to replace the existing CNN model used in the PICS (Pulsar Image-based Classification System). The datasets used for training were HTRU, FAST and PALFA. The model consisted of 15 layers and was again trained and modified for the FAST survey. Earlier, shallow 9-layer and deep 39-layer models were developed. However, they exhibited lower accuracy than the 15-layer ResNet. The 15 layers are divided into one input, two output, and 12 convolutional layers.

The combined training dataset consists of 13632 candidates, out of which 5692 were pulsars, and 7940 were non-pulsars. To verify the generalization of the model, GBNCC and FAST datasets were used during testing. The model worked well for the FAST dataset with recall of 98, however it was 96% for GBNCC data. Hence, the model can be used to replace CNN specifically for FAST dataset, a different approach is required for the model to generalize well on different datasets.

Bao et al [14] proposed a hybrid framework combining GAN and ResNet to solve the class imbalance issue greatly. The GAN model proposed earlier [15] suffers from the 'pattern collapse problem'. The typical GAN sometimes fails to capture the full diversity of target data and instead generates repetitive variations in the generated data. Hence, the [14] proposed Wasserstein GAN to alleviate the pattern collapse problem.

In this hybrid framework, the WGAN model will generate stable pulsar images. These high-quality simulated samples generated will provide better classification features and improve the accuracy of pulsar candidate identification. The ResNet will then identify pulsar candidates using inter and intra-block residual connections. Here, a ResNet with 24 CNN layers is used. Unlike the original ResNet, the proposed network has both inter-module and intra-module residual connections.

The dataset used for training the hybrid framework was HTRU-Medlat with inputs of time-vs-phase and frequency-vs-phase plots. The performance evolution of the model showed better efficiency and accuracy than the GAN and ResNet models proposed earlier. Also, the proposed model has solved the issue of class imbalance to greater extent along with addressing the pattern collapse problem. A precision of 0.983 and 0.993 and recall of 0.980 and 0.974 was achieved for time-vs-phase and frequency-vs-phase input respectively. Table 2 compares various proposed models for pulsar candidate classification.

Table 2. Comparison of Different DL Models

Model	Advantages/Disadvantages	Dataset Used
ANN [8] [9]	Cannot address the class imbalance issue. Poor classification.	[8] - PMPS [9] TGSS and NVSS
CNN [10] [11] [12]	More efficient and accurate than the ANN. Performance is limited due to the class imbalance issue. Most efficient for X-ray sources. Can be used across different surveys.	[10] - HTRU-1 [11] - HTRU [12] - RXTE (Rossi X-ray Timing Explorer)
GAN [15]	Better performance than CNN. Addresses the problem of class imbalance. Performance degraded due to pattern collapse problem.	[15] - HTRU-Medlat and PMPS-26k
ResNet [13]	Solves gradient degradation issue. Hence more efficient than CNN. Cannot solve class imbalance issues as efficiently as GAN. Cannot be easily generalized over different surveys.	[13] - HTRU, PALFA, GBNCC and FAST
Hybrid model (WGAN+ResNet) [14]	Alleviates class imbalance and pattern collapse issues. Efficiency greatly improved for candidate recognition.	[14] - HTRU-Medlat

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4. Conclusion

To conclude, the following insights underscore the significant role of using neural networks in improving pulsar candidate selection.

1. **Efficient Neural Networks:** Amid expanding pulsar datasets, efficient models are essential. Neural networks, notably those discussed, overcome the following challenges of traditional methods.

    i. They significantly reduce the time required for classification by processing several million signals every day.

    ii. These models excel in recall, precision, and F1 score compared to SVM and Decision Trees.

    iii. Reduces the need for human supervision after the pre-processing step.

    iv. Recent hybrid models can be generalized efficiently over different surveys and datasets.

2. **Deep Learning Progress:** Early deep learning efforts used ANN models for candidate selection, showcasing neural networks' promise, but were unable to solve class imbalance issue. CNN models followed, offering reasonable candidate recognition, though efficiency was affected due to the class imbalance problem. However, they showed greater accuracy in X-ray datasets. Then, ResNet was introduced, which stands out with superior accuracy than CNN , but was unable to generalize well over different datasets. GAN followed them, showing higher accuracy than contemporary CNNs, however, its performance was affected due to the pattern collapse problem.

3. **Hybrid Innovations:** Hybrid approaches like WGAN+ResNet showed tremendous potential. The hybrid models surpass the standalone models, addressing class imbalance and pattern collapse problems.

4. **Future Directions:** Ongoing research aims for even more efficient hybrid frameworks, capable of minimal pre-processing for candidate identification. Leveraging cross-survey hybrid samples for training holds promise. These strides promise a precise and efficient path to unravelling cosmic mysteries.

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