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Emerging Trends in Pulsar Star Studies: A Synthesis of Machine Learning Techniques in Pulsar Star Research

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***Abstract*—The pulsar is an extremely magnetized gyrating neutron star having a radius of 10 – 15 km. Pulsars provide the indirect evidence of the gravitational wave's existence. So, to study the gravitational waves identification of pulsars is mandatory. Pulsars are considered as the Universe's gift. Pulsars provide scientists and researchers with information of the physics of neutron stars, which are thought to be the densest materials in the universe. The reason why astronomers give importance to the pulsars, because they are the leading edge of the research, based on the gravity. All pulsars produce marginally distinct emission pattern and it varies to some extent with every rotation. Hence, a promising signal detection is termed as a candidate, which is averaged based on every rotation of the pulsars. Any absence of the additional information, implies that each candidate is a real pulsar. The valid signals are extremely hard to detect due to noise and radio frequency interference (RFI). To clear up with this issue, Machine Learning (ML) algorithms were used for automatically classifying, identifying and many other process of pulsar candidates. This survey paper talks about different techniques used by different researchers for the pulsar star classification, identification and still more, using ML techniques.**

***Index Terms*—Machine Learning, Ensemble Learning, Boosting, Deep Convolutional Network.**

I. Introduction

In the time of 1967, Jocelyn Bell a Ph. D student from Cambridge University and her supervisor Anthony Hewish [1] found something peculiar when they were scrutinizing about the faraway galaxies. When looking at a specific point through the radio telescope, they detected some kind of radio pulses and they named it as Little Green Men 1 (LGM1). Belatedly Little Green Men 1 were entitled as pulsars because of its emission as pulses. At present they are called as the PSR B1919 + 21 [2], discovered on 28 November 1967 when they were working at the university's Mullard Radio Astronomy Observatory (MRAO) [3] and it got the name as first discovered radio pulsar. Within ten to one hundred million years, the electromagnetic energy that these pulsars emit moderately slows down and goes silent. Because of the development and collaboration of the ML in each and every field, there is no astonishment that it can also be widely used in the area of Astronomy.

II. Literature Survey

A. *Astronomy*

Pulsars provided first indirect evidence of the presence of gravitational waves in 1974. M. Bailes, et al. [4] elaborately explained about the operation and the collection of the data by Laser Interferometer Gravitational-Wave Observatory (LIGO) and its international fellows: Virgo and KAGRA. This paper pointed about the extension of gravitational wave detector network globally with the inclusion of LIGO-India project. It gave the catalogue about different gravitational wave events. The paper, provided the elaborate studies of the characteristics of the neutron stars and black hole via gravitational wave observations, providing valuable information of their formation, evolution. So many advanced efforts were taken to identify and study the multi – messenger sources, where gravitational waves were observed in concurrence with another form of radiations like light, X – Rays or may be Gamma rays.

B. *Machine Learning*

Iqbal H. Sarker [5] said that, as we were in the era of Fourth Industrial Revolution, this digital world has millions, billions of data. Those data, can be from the platform of medical, cybersecurity, business, social media etc. For analyzing all these data and to develop related automated applications, the knowledge about ML is very much important. Supervised (S), Unsupervised (US), Semi- Supervised (SS), and Reinforcement Learning (RL) were the different types of ML algorithms. At last, the paper described some of the applications and challenges of ML.

C. *Machine Learning in Astronomy*

Dalya Baron [6] discussed about supervised and un– supervised learning algorithms and mainly focused on un– supervised learning. It furnished the practical information about the ML algorithms and their deployment in the astronomical dataset. The paper described the fundamental concept of supervised learning and un–supervised learning algorithms along with different quality scores and also discussed various supervised learning algorithms used in distinct astronomical tasks plus dimensionality reduction algorithms. This paper talked about feature scaling, how to balance the dataset in case, any presence of imbalanced datasets. The paper gave an applicative idea of how these algorithms can be implemented on different astronomical datasets. The author concluded that, by using un-supervised machine learning algorithm, new unique information can be retrieved from the dataset, which led into the new discovery.

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D. The High Time Resolution Universe Pulsar Survey

M. J. Keith, et al. [7] gave details about the different intriguing objects that have been discovered over the past decade. By deploying the 13 – beam multibeam collector on the Parkes Radio Telescope, they begun the study on pulsars.

The area chosen to take the survey was the complete southern sky in 42641 pointings which has been splitted into three regions as low, mid, high galactic latitude, having the integration times of 4200, 540 and 270s individually. After completing roughly 30 % of the mid latitude survey, they again identified 223 priorly known pulsars and discovered 27 pulsars of which 5 were millisecond pulsars. The data points were observed utilizing Parkes 21- cm Multibeam Receiver (MBR) together with the Berkeley–Parkes–Swinburne Recorder (BPSR) backend system. For processing the survey, they devised the processing pipeline called HITRUN.

E. Classification of Pulsars

1) Machine Learning for classifying Pulsar Stars

A branch of Artificial Intelligence (AI) [8] is Machine Learning, mainly concentrated on the usage of the predefined data and algorithms to imitate in the way the human behaves. ML is used in the areas of Autonomous Vehicles, Speech Recognition, detecting Fraud and in other fields also. Using the model historical data, said to be the training data, algorithms of ML were used to construct a mathematical model, to make predictions or decisions without programming externally. The concept of ML for pulsar classification is shown in Figure1.

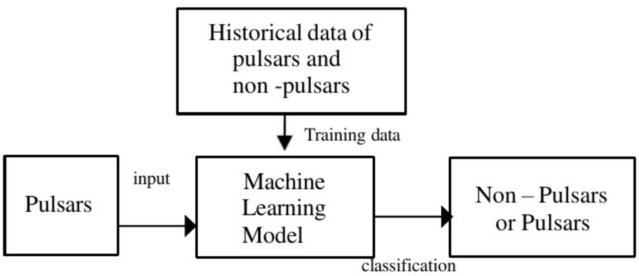

Fig. 1. General Model describing the classification of historical pulsar dataset

Right now, various researchers are using different ML methods for the purpose of pulsar star classification, identification, etc. Different ML algorithms [9] used for pulsar classification includes Random Forest (RF), Decision Tree (DT), Naive Bayes (NB), Artificial Neural Network (ANN) and other algorithms.

2) Classification of Pulsars using Extreme Gradient Boosting and Light Gradient Boosting

Tariq, et al. [10] used HTRU2 [11] and LOTAAS – 1 datasets. For handling the class imbalance problem, asymmetric under sampling method was applied. For sampling the majority class in the aspect of equal basis, imbalance ratio (IR) of pulsar dataset was defined. The hyperparameters of XGBoost (XGB) and LightGBM (LGBM) were tuned by the validation data for selecting the best model. The suggested model performance was related with other classifiers such as Support Vector Machine (SVM), Multilayer Perceptron (MLP), NB, Pseudo Nearest Centroid Neighbor (PNCN) [12] classifier and at last the Gaussian Hellinger Very Fast Decision Tree (GH –VFDT).

Performance results on HTRU2 and LOTAAS - 1 dataset:

In HTRU2, XGB surpassed the other classifiers with the accuracy of 0.981 where LGBM achieved the accuracy of 0.980. Here in the case of LOTAAS – 1 dataset, both XGB and LGBM produced the same level of accuracy which is 0.999.

3) Classification of Pulsars using Deep Convolutional Neural Network (DCNN)

Yuan – Chao Wang, et al. [13] deployed DCNN, having different layers like:

- Convolutional – Eight
- Flatten - One
- Completely connected – Two

which was totally eleven layers. This proposed model was implemented on the HTRU 1 dataset. To address the class imbalance issue, oversampling technique based on minority synthetic sampling was deployed. For visualizing the samples, t – distributed Stochastic Neighbor Embedding (t – SNE) [14] was employed. Results obtained using DCNN model without synthetic samples achieved the recall of 0.851 and the precision of 0.848. The DCNN model with synthetic samples obtained the recall of 0.962 and precision of 0.963.

4) Classification of Pulsars utilizing Artificial Neural Network and Support Vector Machine

Thomas Ryan Devine, et al. [15] used ANN and SVM for classification. ANN classified instances by implementing the back propagation method and sigmoid as an activation function in every neural node.

Using SVM as an iterative training procedure, the error function was decreased. The divide and conquer strategy helped to reduce error.

5) Classification of Pulsars using a framework of Deep Convolutional Generative Adversarial Network (DCGAN) with Support Vector Machine

Ping Guo, et al. [16] used an architecture that combined SVM and a DCGAN. In this case, for generating the sample and for the purpose of feature learning model, DCGAN is deployed and SVM is used as a classifier to predict the label of the candidate.

6) Classification of Pulsars using Hybrid Ensemble Method

Y. Wang, et al. [17] used three ensemble methods. They were RF, XGB and Hybrid Ensemble method. HTRU 1 and HTRU2 dataset was used. In Hybrid Ensemble method, RF and XGB were integrated with Easy Ensemble. The problem of class imbalance was resolved using Easy Ensemble, which was also used to enhance the model's stability.

7) Classification of pulsars using different machine learning algorithms

Jin Rong Song [18] discussed various ML algorithms for classifying the pulsar stars. SVM, CNN, Gaussian NB, Logistic Regression (LR), DT, RF were deployed to classify the pulsar stars. Eight unique attributes and one target class were present in dataset, which had 12528 data values. The author employed two unique features to handle the missing data, i.e., drop (DR) method and average value (AV) method. The paper provided the results, obtained using both the DR method and AV method. Logistic Regression achieved the highest accuracy in classifying, with the accuracy rate of 0.99, when using DR method. In case, when replacing the missing value with AV method, SVM and CNN with 5 layers and 50epochs achieved the highest accuracy of 0.98.

8) Classifying pulsars and ranking the candidates for Fermi2FGL catalog

K. J. Lee, L. Guillemot, et al. [19] mainly focused on Bayesian data classification algorithms which used the Gaussian Mixture Model (GMM). Neyman-Pearson test was used for determining the data classification technique.

In the ranked list, the topmost 5 percent sources contained 50percent known pulsars, the topmost 50 percent contained 99 percent known pulsars. The GMM was tested by using the multi-dimensional Kolmogorov-Smirnov test. The paper discussed about the GMM and its applications in data modelling and classification, for instance it was

applied in P-$P^{\cdot}$ diagram for pulsar classification, in addition, modelling and ranking the 2FGL catalog point sources. Authors also conveyed, about the implications of the clusters, founded by GMM algorithm.

F. Detection of Pulsars

1) Detection of pulsar candidates – different classification algorithms were compared using SMOTE

Apratim Sadhu [20] utilized a variety of ML techniques, including LR, K-NN, SVM, DT, RF, Bagging, XGB, Adaptive Boosting, and Gradient Boosting. The techniques were implemented on HTRU2 dataset. Deploying 10-fold cross-validation method, the methods were implemented and compared. 90 percent of the total samples were used as training data and balance 10 percent was considered as test data. To overcome class imbalance problem, minority class got over-sampled using the oversampling technique called SMOTE. In case of unbalanced dataset, XGB achieved the highest accuracy of 0.9797, whereas in SMOTE balanced dataset, XGB had the highest accuracy rate of 0.9732. Artificial Neural Network was also implemented with 9 layers and achieved the accuracy of nearly 98%.

2) Detection of Pulsar Candidates deploying Bagging Method

Mourad Azhari, et al. [21] connected the Bagging Method with primary classifiers: Core Vector Machines (CVM), K-NN, ANN, and Cart Decision Tree (CDT). For implementing the classifiers, HTRU2 dataset was used. Herein this case, Bagging algorithm worked in the level of two phases:

- Phase I -Training
- Phase II -Testing

To overcome imbalance issue, resampling techniques were used in the manner of data split and k fold CV. For the purpose of training and testing, the samples were divided into 70 percent and 30 percent respectively. The value of k in k fold cross validation was chosen as 10. The authors compared among the basic classifiers and also compared Bagging with different classifiers. Taking AUC metric into consideration, KNN (0.994) achieved better than others. In case of Bagging, Bagging (K-NN) (0.9913) outperformed others.

3) Detection of pulsars Feed Forward Backpropagation (FFBPN) and Cascade Forward Backpropagation Neural Network (CFBPN) Algorithms

Fahriye Gemci Furat, et al. [22] used HTRU_2 dataset to classify the pulsar by implementing, FFBPN and CFBPN algorithms. 8 features of the dataset were given as input to the neural networks. Hidden layer was assigned with 10 hidden neurons. Table I shows accuracies of both FFBPN and CF-BPN.

Table I. Accuracies of Ffbpn and Cfbpn

Neural Network	FFBPN	CFBPN
Classification Accuracy – Training Data (TRD)	91.022	95.3704
Classification Accuracy – Testing Data (TED)	92.336	90.692

4) Detection of pulsars with few features using machine learning

Haitao Lin, et al. [23] proposed feature selection algorithms, to enhance the detection performance, Grid Search (GS) and Recursive Feature Elimination (RFE) were deployed by eliminating the unnecessary and redundant features. The algorithms were implemented on Southern High Time Resolution University survey (HTRU-S), which contained 1196 pulsars and 89996 non-pulsars with 18 features. For training, 50% of the data was used, denoted as NON-SAMPLING. The balanced training dataset were obtained by undersampling, oversampling and SMOTE which were termed as UNDERSAMPLE, OVERSAMPLE, SMOTE. Different models used in this paper were: Classification and regression tree (CART), Adaptive boosting (AdaBoost), Gradient boosting classifier (GBoost), XGB, RF. Except for RF, GS was applied. Grid Search (GS) and Recursive Feature Elimination (RFE) algorithms were applied to single, double features and also to multiple features. Both training and testing were splitted into 50% and were normalized, prior to giving them as input to the models. Then feature selection was done and the models were trained on the basis of the proposed feature selection algorithms. On the training data, five fold cross-validation was performed. A model having just two features from GS had a recall rate of up to 99 percent. A model with three features had a 99 percent recall rate when using RFE.

G. Prediction of Pulsars

1) Predicting pulsars with hybrid resampling approach

Ernesto Lee, et al. [24] used various supervised ML algorithms, for detecting true pulsar candidates. For implementation, HTRU2 dataset was used. Table II shows in detail about accuracies with different resampling approaches. As the dataset was imbalanced, two resampling methods were used: SMOTE, Adaptive Synthetic Resampling (ADASYN).

TABLE II. DETAILS ABOUT ACCURACIES WITH DIFFERENT RESAMPLING APPROACHES

S. No	Details	Best	Accuracy
1	Without data resampling	Random Forest Logistic Regression	0.980
2	CC data resampling	Random Forest	0.943
3	SMOTE	Extra Tree Classifier	0.982
4	CR data resampling	Extra Tree Classifier	0.993
5	ADASYN	Extra Tree Classifier	0.981

And to minimize the size of majority class, Cluster Centroid(CC) undersampling method was employed. So, this hybrid resampling method or concatenated resampling (CR) method was suggested to solve class imbalance issue. Different ML models used in this paper were: RF, Gradient Boosting Classifier (GBC), Extra Tree Classifier (ETC), LR, MLP. Resampling was performed before splitting in the proportion of 70:30. Resampling was implemented on the training set. After completion of data resampling and data splitting, the given ML models were trained using 70 percent data. The remaining 30 percent was deployed for testing the trained models. The paper gave the details about the comparison of ETC with different resampling methods, when the data was splitted prior to data resampling. Deep learning models such as: long short-term memory (LSTM), deep neural network (DNN) and gated recurrent unit (GRU) also implemented, where each of them achieved the same accuracy of 0.98. In addition, 10-fold cross- validation was also implemented. Statistical T-test was also implemented to showcase the importance of CR technique.

H. Pulsar candidate selection to classification

R. J. Lyon, B. W. Stappers, et al. [25] suggested that enhancing the survey recommendations caused rise in pulsar candidate numbers and also data volumes. Candidate filters were deployed to solve those problems during the last 50 years. Here a new technique was proposed for online operation, which selected only positive candidates. This selection could be implemented using, Gaussian Hellinger Very Fast Decision Tree along with new set of features for describing candidates. With these properties, the suggested technique had a better level of pulsar recall and could execute millions of candidates in seconds. LOTAAS 1, HTRU 1, HTRU 2 datasets were used. Other ML methods were used to compare with the proposed method, they are: C4.5, MLP, NB, SVM. table III gives the details about the accuracies with different datasets.

TABLE III. DETAILS ABOUT THE ACCURACIES WITH DIFFERENT DATASETS

S. NO	DATASET	CLASSIFIER	ACCURACY
1	HTRU 1	GH-VFDT	0.988
2	HTRU 2	GH-VFDT	0.978
3	LOTAAS 1	SVM	0.999

I. Machine learning pipeline

Alexander Ylnner Choquenaira Florez, et al. [26] used HTRU2 dataset for implementing different ML algorithms. The techniques included: Data-Analysis, Pre-Processing, Sampling, Processing. The algorithms used were: NB, LR, DT, Perceptron, MLP, SVM. Various ensemble techniques were also implemented, such as: Stacking, Bagging, RF. For conducting various experiments, the authors divided HTRU2 dataset into 3 variations. Table IV gives details about variations of the dataset.

TABLE IV. DETAILS ABOUT VARIATIONS OF THE DATASET

S. NO	DATASET	CLASSIFIER	ACCURACY
1	HTRU 1	GH-VFDT	0.988
2	HTRU 2	GH-VFDT	0.978
3	LOTAAS 1	SVM	0.999

In the experiment 2, authors considered only 6 features (feature selection) which followed the correlation proportion between them. Other than accuracy, Precision and Recall was also used as quality factors.

After implementing with K-Fold Cross Validation with k = 10, following models showed different accuracies. table V. gives details about accuracies achieved by different models in different variations of the dataset.

TABLE V. DETAILS ABOUT ACCURACIES ACHIEVED BY DIFFERENT MODELS IN VARIATIONS OF THE DATASET

Dataset	Model	Accuracy
Dataset1	LR	0.98
	DT	0.98
	XGB	0.98
	Bagging	0.98
	Gradient	0.98
Dataset2	XGB	0.95
Dataset3	XGB	0.95

The table VI. shows accuracies with feature selection.

TABLE VI. ACCURACIES WITH FEATURE SELECTION

Dataset	Model	Accuracy
Dataset1	DT	0.98
	SVC-RbfK	0.98
	XGB	0.98
	RF	0.98
	Bagging	0.98
	Gradient	0.98
Dataset2	XGB	0.95
Dataset3	Bagging	0.97

The Table VII. shows different articles using different techniques on the pulsar dataset.

III. DISCUSSION & CONCLUSION

Pulsar signals are most often very weak which can be easily drowned out by any other astrophysical sources or background noise. So, differentiating pulsar signals from RFI or from any other natural radio emissions from the galaxy is a very difficult task. From the reviews, the future work can be suggested that, different Ensemble Learning techniques such as Stacking, Voting Ensembles, Blending and quantum ML can be used to classify, identify, searching and for different operations on the pulsar stars. This paper reviews the meth-

TABLE VII. DIFFERENT ARTICLES USING DIFFERENT TECHNIQUES ON THE PULSAR DATASET

S. NO	PAPER TITLE	DATASET	TECHNIQUES DEPLOYED	YEAR
1	Pulsar Classification: Comparing Quantum Convolutional Neural Networks and Quantum Support Vector Machines	HTRU-2	1. Quantum Kernel assisted Support Vector Machines (QSVMs) 2. Quantum Convolutional Neural Networks (QCNNs)	2023
2	Pulsar Candidate Classification Using a Computer Vision Method from a Combination of Convolution and Attention	FAST	CoAtNet-MLP-LR	2023
3	MFPIM: A Deep Learning Model Based on Multimodal Fusion Technology for Pulsar Identification	FAST	1. MFPIM-ResNet 2. MFPIM	2023
4	Advances in Pulsar Candidate Selection: A Neural Network Perspective	• PMPS • TGSS and NVSS	ANN	2023
		• HTRU-1 • HTRU • RXTE (Rossi X- ray Timing Explorer)	CNN	
		• HTRU-Medlat • PMPS26k	GAN	
		• HTRU • PALFA • GBNCC [27] • FAST	ResNet	
		• HTRU-Medlat	Hybrid model (WGAN+ResNet)	
5	Classical Ensembles of Single-Qubit Quantum Variational Circuits for Classification	HTRU 2	1. Bagging Ensemble 2. Boosting Ensemble 3. Single QAUM	2023
6	Random Forest Identification of Pulsars	HTRU2	1. Random Forest 2. Balanced the dataset: SMOTE and Subset of Noise	2023
7	A Pulsar Search Method Combining a New Feature Representation and Convolutional Neural Network	Self-Collected RXTE observation data	1. ConvNets - to learn 2D spatial information of the new pulsar feature representation and to classify them 2. Non-Homogeneous Poisson Process - provide training set for ConvNets 3. GAN – for data augmentation	2022
8	AdaBoost-MICNN: a new network framework for pulsar candidate selection	High Time Resolution Universe Medlat Data	AdaBoost-multi-input-CNN (AdaBoost-MICNN)	2022
9	Adaboost-DSNN: an adaptive boosting algorithm based on deep self normalized neural network for pulsar identification	HTRU-1 and HTRU-2	1. Deep Self Normalized Neural Network (Adaboost-DSNN) 2. Synthetic Minority Oversampling TEchnique (SMOTE) – to balance the dataset	2022
10	Pulsar-candidate Selection Using a Generative Adversarial Network and ResNeXt	HTRU Medlat	Combination of Deep Convolutional Generative Adversarial Neural Network (DCGAN) and a Deep Aggregation Residual Network (ResNeXt)	2022
11	Pulsar candidate selection with residual convolutional autoencoder	• HTRU Medlat • PMPS-26k	1. Residual Convolutional Autoencoder (Rcae) 2. Logistic Regression (Lr)	2022
12	Pulsar identification based on generative adversarial network and residual network	HTRU-Medlat	1. Generative Adversarial Networks – To handle class imbalance problem 2. deep neural network – using intra- and inter-block residual connectivity – recognition accuracy	2022
13	Stellar and Pulsar Classification using Machine Learning	HTRU	1. k-NN 2. Decision Tree 3. Random Forest	2021
14	Quantum Machine Learning for Radio Astronomy	HTRU 2	Born machine (Quantum Neural Network)	2021
15	Concat Convolutional Neural Network for pulsar candidate selection	FAST	Concat Convolutional Neural Network	2020

ods used for pulsar classification, identification, selecting and separating mainly on the basis of ML, talked about some of the problem that needs to be solved and proposed some methods that can be carried out on the pulsar stars.

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