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Machine Learning Application for the Classification of Solar Radio Bursts

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1. ABSTRACT

Solar radio bursts impact society's technical infrastructure and environment. This study investigates Solar Radio Bursts and builds a deep neural network to classify the bursts according to their main five types. Manual classification of solar radio bursts is challenging due to continuous 24-hour observation and noises in spectrograms. Thus, a deep neural network was implemented to classify main types I, II, III, IV, and V. FITS files from the e-Calisto network were used as raw data. Gaussian, erosion, dilation, and thresholding techniques were used to reduce the noise of images and get clearer spectrograms. Initially, a Convolutional Neural Network model was used to classify spectrograms as bursts or non-bursts, achieving a validation accuracy of 98.55% and a loss of 8.15%. Subsequently, features were extracted from bursts and classified by their types using pre-trained CNN models VGG16, ResNet, and AlexNet. The training accuracy and loss values for VGG16, ResNet, and AlexNet were 98.72% and 5.87%, 86.50% and 40.90%, 90.93% and 26.88%, respectively. Validation accuracy and loss were 87.8% and 33.35% for VGG16, 73.61% and 81.9% for ResNet, and 76.9% and 77.24% for AlexNet. Among the models, VGG16 with ImageNet proved the most effective for burst-type classification based on confusion matrix, accuracy, and loss values. The obtained results can facilitate the development of a fully automated system with a user interface for classifying solar radio bursts and extracting their primary features. Furthermore, this finding can be utilized to create a database that classifies solar radio bursts recorded since 1978.

2. INTRODUCTION

Solar flares release immense amounts of energy, resulting in the heating of the solar atmosphere and causing disturbances in Earth's ionosphere [1]. The identification and classification of solar radio bursts play a crucial role in predicting space weather events that can disrupt satellites, power grids, and communication systems. Solar activity can severely impact GPS accuracy, aviation operations, and radio communications.[2] These disruptions can interfere with radio signals, degrade GPS accuracy, and, in extreme cases, cause radio blackouts or damage satellites and spacecraft. By accurately detecting and categorizing these bursts, we can enhance space weather forecasting, enabling timely precautions to protect critical infrastructure and technological systems.[3] Solar radio bursts, which are sudden emissions of electromagnetic radiation from the Sun, are typically linked to solar flares and coronal mass ejections (CMEs), violent expulsions of plasma and magnetic energy. These bursts are classified into five distinct types: Type I (noise storm), Type II (slow drift), Type III (fast drift), Type IV (broadband continuum), and Type V (continuum at meter wavelengths).

Historically, classifying these bursts has been a complex, manual process due to the unique characteristics of each burst. To automate this task, deep learning techniques have been applied. Deep learning, a subset of artificial intelligence, leverages neural networks to automatically extract features and make predictions. For this study, spectrogram data from the e-Callisto international network, which provides continuous solar corona monitoring, serve as the primary data source. These data, spanning back to 1978, include essential information such as frequency ranges and intensity levels.

This research utilizes Convolutional Neural Networks (CNNs) to first determine whether a spectrogram contains a burst and subsequently classify the burst type. Pretrained models, such as ImageNet, were fine-tuned for this specific task, and the models' performance was evaluated to identify the most effective architecture for accurate classification [11].

3. METHODOLOGY

3.1 Pre-requirements

The study began with an in-depth exploration of solar radio bursts, focusing on their types, formation mechanisms, and impact on satellite communication. Additionally, the e-Callisto network and its FITS file format were studied, along with image processing techniques and machine learning models required for classification tasks. Data from the e-Callisto database, specifically FITS files recorded between 2020 and 2023, were collected using Python scripts and the BeautifulSoup library. These files were organized and labeled into five categories corresponding to solar radio burst types for efficient processing and analysis [4].

3.2 Preprocessing

FITS files were converted into PNG images using Python libraries such as Astropy, Matplotlib, NumPy, and PIL. In these images, frequency and time data were mapped to the axes, while intensity values were visualized as pixel intensities [7]. To enhance the image quality, a Gaussian filter with a sigma value of 1 was applied to reduce noise. Thresholding based on the mean intensity values was then performed, resulting in binary images where significant intensity values appeared as white pixels. Morphological operations were used to further refine the images, binary erosion with a 3×3 kernel was applied to remove noise and shrink object boundaries, followed by dilation to expand and enhance the foreground regions. These steps improved the clarity of the binary images, which were subsequently saved with labels in designated folders for burst detection and classification [5].

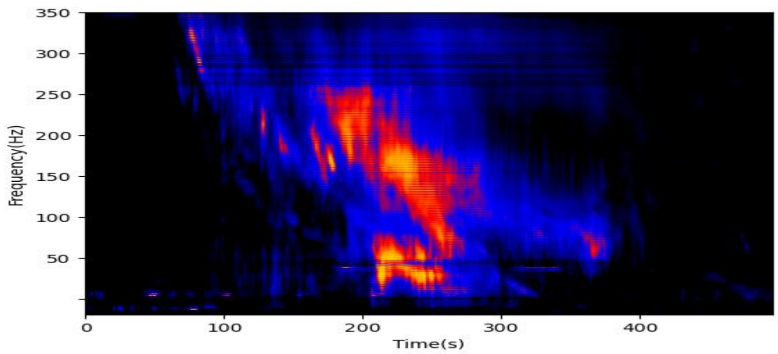


Figure 1: Solar radio burst PNG format representation with the axis

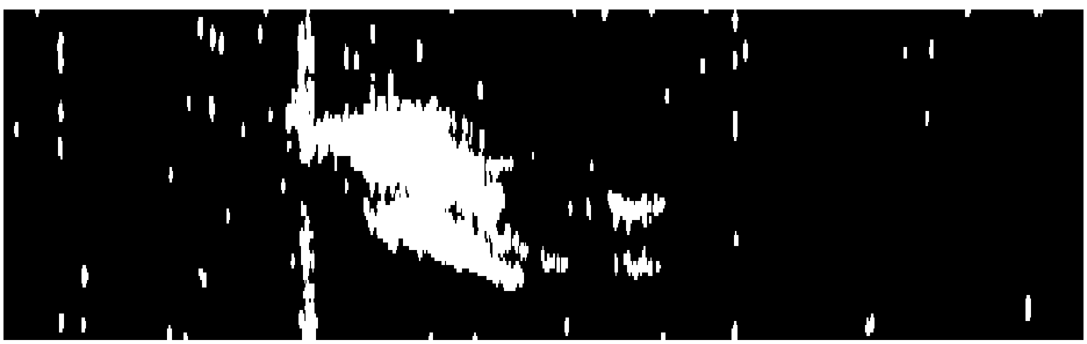


Figure 2: Preprocessed solar radio burst image. Noises were eliminated using Gaussian, erosion, dilation, and thresholding techniques.

3.3 Burst Identification

Initial attempts at identifying bursts used image processing techniques based on intensity gradients and time frames. However, these methods were insufficient due to low true positive and negative rates. To address the limitations of traditional techniques, a Convolutional Neural Network (CNN) was implemented using TensorFlow and Keras [8]. The dataset was prepared by resizing images to 128×128, converting them to grayscale, normalizing pixel values, and encoding labels. The data was then split into 80% training and 20% testing subsets [10]. The CNN architecture featured convolutional, max pooling, and dense layers optimized with the Adam algorithm and binary cross-entropy loss. The model was trained over 10–20 epochs with a batch size of 32, successfully classifying images as "burst" or "no burst," enabling further categorization of solar radio burst types [6].

3.4 Burst type identification using VGG16 model

The VGG16 model is a widely used CNN architecture for image classification, object detection, and feature extraction. It comprises 16 convolutional layers, max-pooling layers, and three fully connected layers with 4096 neurons each. Convolutional layers preserve spatial information while max-pooling layers extract relevant image features. [13] ReLU activation functions are applied in all layers except the last, which uses the SoftMax activation function for multi-class classification. Pre-trained on the ImageNet dataset, VGG16 supports RGB images and adjusts layer weights through backpropagation and gradient descent [9].

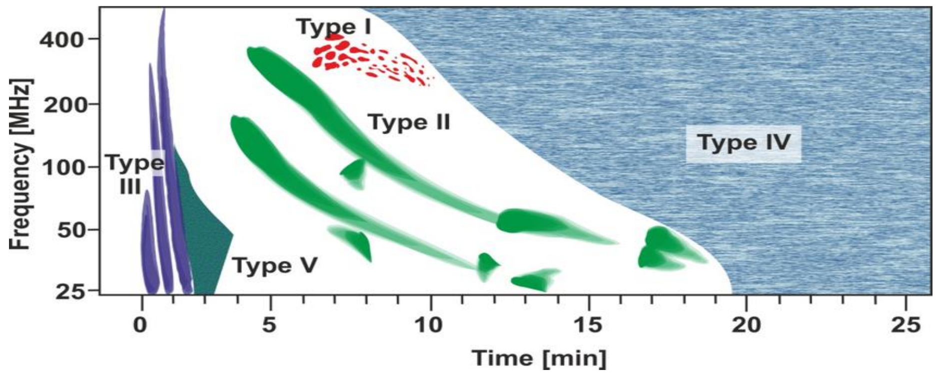


Figure 2 : Burst-type representation with their frequency regions.

4. RESULTS AND DISCUSSION

4.1 Burst identification

The model demonstrated excellent performance in classifying images as "burst" or "no burst," achieving a test/validation accuracy of 98.35%, a training accuracy of 99.12%, a test/validation loss of 0.0815, and a training loss of 0.0165. Test accuracy reflects the model's ability to generalize to unseen data, with a high value indicating reliable predictions, while training accuracy highlights its effectiveness in correctly classifying the training dataset. Loss metrics, including training and validation losses, measure the difference between predicted and true outputs, with low values confirming minimal error and effective learning. As shown in the training curve, the model's accuracy steadily increased with each epoch, reaching 99.12% on the training dataset, and validation accuracy of 98.35% confirms the model's strong generalization capability for unseen data.

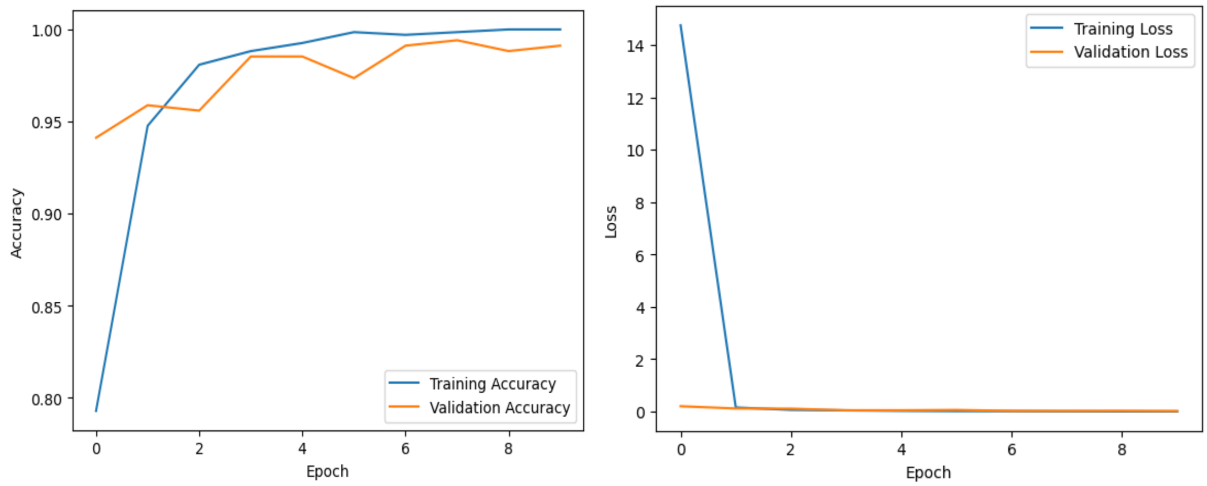
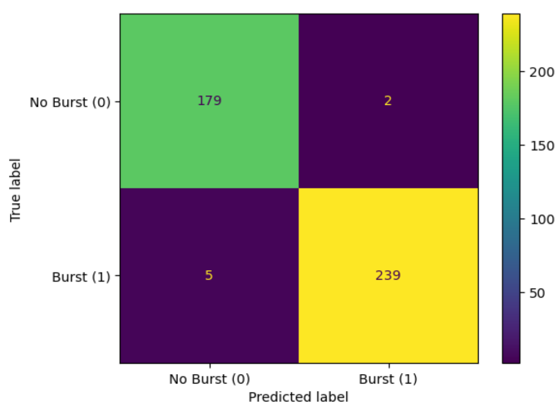


Figure 3 : Accuracy and loss value variation of VGG16 model.

A confusion matrix is used to visualize the model's performance. The confusion matrix for obtained results is as follows,



Confusion Matrix :	
True Positive (TP)	: 239
True Negative (TN)	: 179
False Positive (FP)	: 2
False Negative (FN)	: 5

Figure 4 : Confusion matrix explained with values.

The model predicts an actual burst as a burst in 239 instances and actual no-bursts predicted as no-bursts in 179 instances. Model incorrectly predicted burst as non-burst in 5 instances and incorrectly predicted non-burst as a burst in 2 instances. Then the model was saved to make predictions on unseen data. The threshold value probability is set as 0.5 and the model should predict unseen data as a burst or not a probability larger than 0.5. Below are some results obtained for the predictions for unseen data.

4.2 Burst type identification

The VGG16 model yielded a train accuracy of 98.72% and a train loss of 5.87%. As a result, it is accurate in classifying already-seen images, and the model's variance is acceptable. The validation model successfully classifies unseen images with a probability of 87.8%, while there is a small variation between predicted and actual labels with a probability of 33.35%.

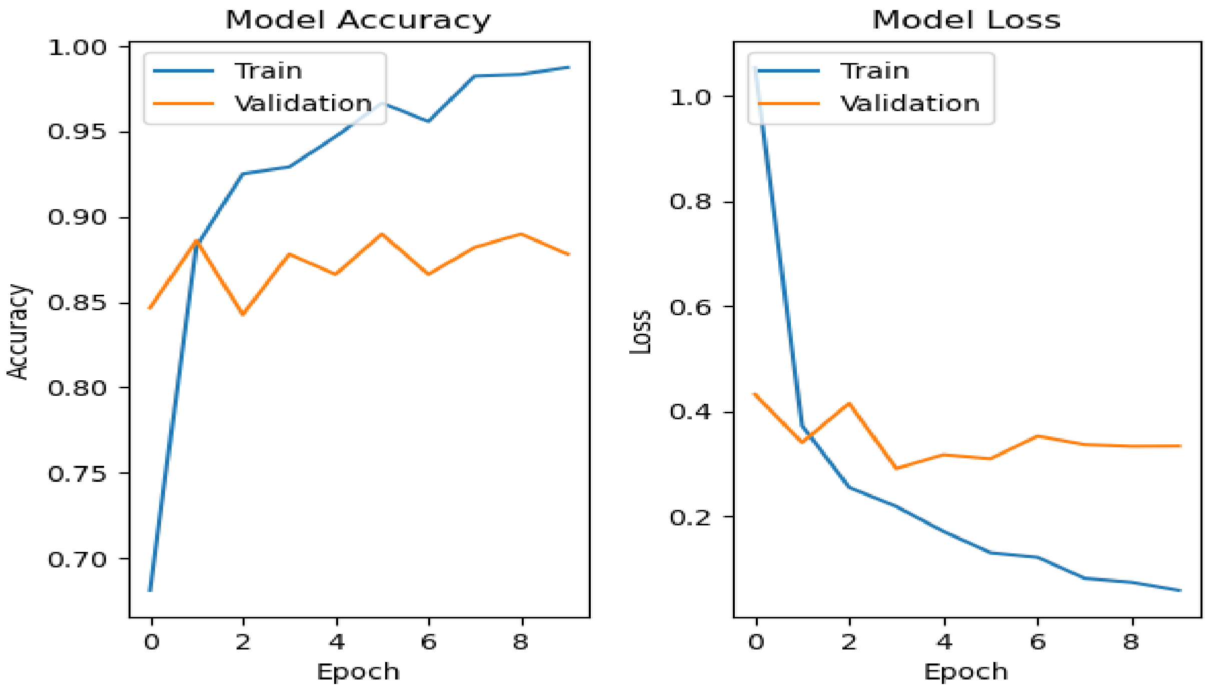


Figure 5: VGG16 Model's accuracy and loss with several epochs.

Table 1- True positive, True negative, False positive, and False negative values obtained for VGG16 with ImageNet

	Type II	Type III	Type IV	Type V
True Positives	77	96	2	48
True Negatives	158	139	245	189
False Positives	11	12	0	8
False Negatives	8	7	7	9

Table 2 : Classification report of the VGG16 model for each type of burst

	Precision	Recall	F1-Score	Support
Type 2	0.88	0.91	0.89	85
Type 3	0.89	0.93	0.91	103
Type 4	1.00	0.22	0.36	9
Type 5	0.86	0.84	0.85	57
Accuracy			0.88	254
Macro Avg	0.91	0.73	0.75	254
Weighted Avg	0.88	0.88	0.87	254

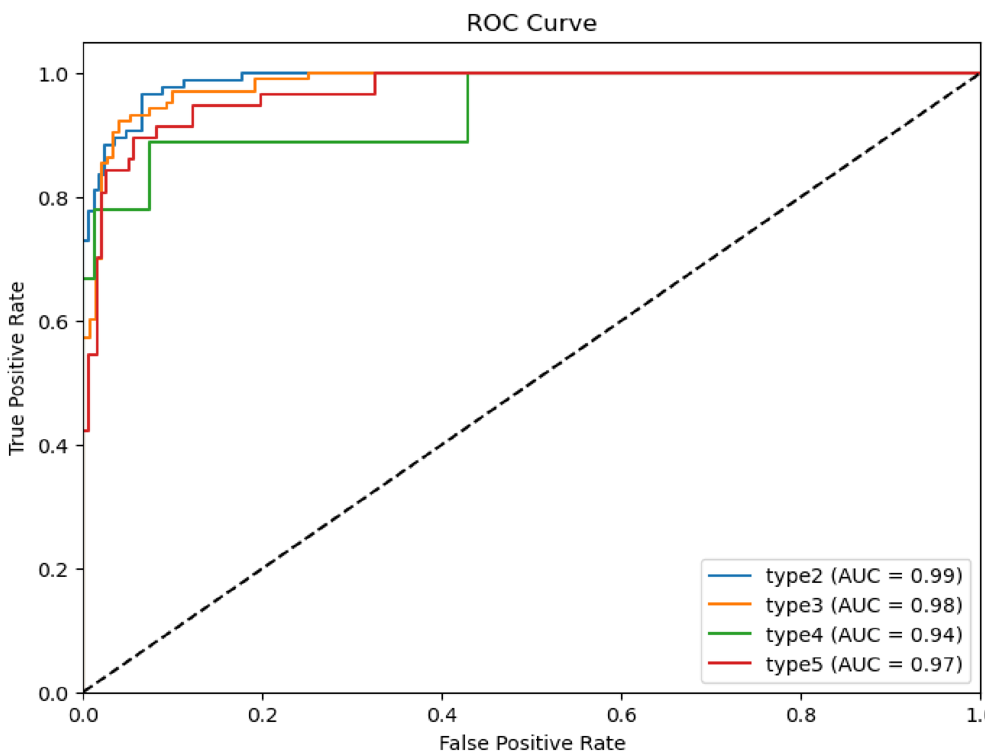


Figure 6 : ROC Curve of VGG16 model.

The classification report highlights the model's performance across different burst types. While types II, III, and V showed high precision, recall, and F1-scores (88-100% precision, 84-93% recall, and 85-91% F1), type IV performed poorly due to its low recall (22%) and limited support. Precision measures the accuracy of positive predictions, recall evaluates the model's ability to identify all positive instances, and the F1-score balances both metrics. The overall results indicate good performance for types II, III, and V, but the low support for type IV limits the model's effectiveness in identifying this class.

The ROC curve used to visualizes the relationship between the True positive rate (TPR) and False positive rate(FPR) across different threshold values. This ROC curve is considered a perfect curve if it passes through the upper left corner (TPR=1, FPR=0). It indicates high sensitivity and a low false positive rate. The area under the ROC curve shows the overall performance of the model. The higher AUC shows better adaptability. AUC value closer to 1 represents a good model.

Compared to the other two models, VGG16 demonstrated superior performance with the highest accuracy and the lowest loss values. This highlights its effectiveness in feature extraction and classification tasks, making it the most reliable model for the dataset under consideration. The architecture's depth and robust design contribute to its ability to generalize well, outperforming both ResNet and AlexNet in terms of predictive accuracy and minimizing error.

4 CONCLUSION

This study explored the classification of Solar Radio Bursts using machine learning, focusing on identifying and categorizing burst types. Spectrograms were first classified as burst or no burst using the VGG16 model with ImageNet, followed by the evaluation of three machine-learning models for burst-type classification. VGG16 demonstrated the best performance, effectively identifying bursts and categorizing them. Previous studies have used machine learning models to classify FITS images as either containing a burst or not. However, no research has focused on classifying these bursts into the five main types. This model achieves a validation accuracy of 98% and a loss value of 8.15% for distinguishing bursts or non-bursts, demonstrating superior performance compared to other studies. Type I images were excluded from the study due to the absence of satellite capturing. While the model performs well in classifying the five main burst types, achieving a validation accuracy of 87.8%, the lack of Type IV compared to other types, results in a significant loss value of 33.35%. This loss can be reduced by supplying more Type IV burst images to the model. The findings highlight the potential to improve results by including more type IV images and suggest extending this work to build a comprehensive Solar Radio Burst database. These advancements could enable automated classification systems to predict and mitigate the impact of bursts on Earth's ionosphere.

5 REFERENCES

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