**OPTIMIZING METEOR DETECTION WITH MACHINE LEARNING.** S. Anghel<sup>1,2</sup>, D. A. Nedelcu<sup>1,2</sup> and M. Birlan<sup>1,2</sup>, <sup>1</sup>Astronomical Institute of the Romanian Academy (5 Cuțitul de Argint, 040557 Bucharest, Romania Simon.Anghel@astro.ro), <sup>2</sup>Institut Mécanique Céleste et de Calcul des Éphemerides (IMCCE), Observatoire de Paris (77 Avenue Denfert-Rochereau, 75014 Paris, France).

**Introduction:** In recent years, the increasing availability of automated data collection, coupled with advances in computational power, has led to the widespread implementation of machine learning (ML) techniques across numerous fields. The field of meteor science is no exception, where accurate detection and identification of meteors can be challenging, particularly in single-station observations where false positives may be as high as an order of magnitude greater than true meteoric phenomena. To address this issue, in this study, we explore the application of ML models to re-analyze single-station observations of meteors with the goal of identifying and extracting genuine meteoric events.

**Methods**: The data was obtained from the Meteorites Orbits Reconstruction by Optical Imaging Network (MOROI) installed across Romania [1], [2]. For the purpose of this study, we built a dataset of events recorded during a period of three years (2017-2020). Next, a set of 15 ML models were trained using features extracted from meteor movement across the CCD. The models were chosen based on their ability to classify tabular data, allowing the bundle of ML techniques to be applicable to other studies. The selected features are independent of the camera configuration, allowing for scalability and application to other networks. To obtain the performance of the classification, we tested the ML models via a stratified-k-fold validation and evaluated the results using a series of metrics [3].

**Results**: From the set of 24 features computed for each event, 7 were found relevant for increasing the score. These were obtained via a *keep-best* method which cycled through the features while testing the classification accuracy. After model selection and hyper-parameter toning, we found that the best performing models reached a top classification accuracy score of 98.2% and a recall score of 96% (Figure 1). Combining the spatiotemporal coincidence of detections further increased the recall score to 99.92%. Importantly, the bundle of 15 ML models and computed features have the potential to be applied to other camera networks and studies.

**Discussion**: The difference in performance across the models is caused by several reasons. Models such as Linear SVM and Radial Bayesian Function SVM may be more sensitive to outliers, while Ridge and Quadratic Discriminant Analysis are prone to overfitting, which leads to a lower performance. In contrast, ensemble models like Gradient Boost and Random Forest are less sensitive to outliers and can better handle noisy data and imbalances between classes i.e., the meteor to nonmeteor ratio of 1:5 in our data set. Nevertheless, the top results of the models demonstrate the potential for reanalyzing single-station meteor detections, a valuable and previously neglected data source, quite important when measuring the flux of objects on a given area. Further, the ability to apply these techniques to other networks and studies will increase the efficiency of meteor analysis.

	Accuracy	Precision	Recall	F1	Specificity	
Nearest Neighbors	0.97	0.87	0.94	0.90	0.98	
Decision Tree	0.97	0.90	0.89	0.89	0.98	
Extra Tree	0.97	0.91	0.87	0.89	0.98	
Adaboost -	0.98	0.91	0.93	0.92	0.98	- 0.95
Gradient Boost	0.98	0.92	0.95	0.93	0.99	
Random Forest	0.98	0.93	0.95	0.94	0.99	- 0.90
Stacking Estimators	0.98	0.92	0.94	0.93	0.99	
Neural Net	0.98	0.89	0.96	0.92	0.98	- 0.85
Gaussian NB	0.54	0.23	0.91	0.37	0.48	
Linear SVM	0.89	0.78	0.38	0.51	0.98	- 0.80
RBF SVM	0.92	0.79	0.64	0.71	0.97	
QDA -	0.62	0.27	0.91	0.42	0.57	0.75
Perceptron -	0.88	0.58	0.69	0.63	0.91	0.75
Ridge -	0.78	0.40	0.97	0.56	0.74	
Stochastic GD	0.92	0.79	0.66	0.72	0.97	0.70

Figure 1. The classification results computed for all models. The scores are averaged over a total of 10 runs and displayed as a heatmap.

Conclusion: Our study shows that the use of ML models can provide an optimal method for re-analyzing single-station observations and identifying real meteors from multi-station detections. The feature extraction method is designed to be scalable, and can be applied to other networks and studies. We look forward to implement these techniques to re-analyze events the Fireball recorded within Recovery and InterPlanetary Observation Network (FRIPON) consortium [4] and beyond, ultimately leading to a better understanding of the nature and behavior of meteors.

**References:** [1] Nedelcu D. A. et al. (2018) *Romanian Astronomical Journal* 28:1:57-65. [2] Anghel S. et al. (2021b) *in LPI Contributions Vol. 84*, Abstract #6027. [3] Anghel S. et al. (2023) *Monthly Notices of the Royal Astronomical Society* 518:2810. [4] Colas F. et al. (2020) *Astronomy & Astrophysics* 644:A53.