

EXO-INSIGHT: Explainable Multi-Modal Deep Learning Framework for Exoplanet Detection

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Abstract- Because of the rapid increase in astronomical observation missions, a huge amount of data is generated, which should be analyzed to detect exoplanets that may be present in the data. Space-based telescopes such as the Kepler mission and the Transiting Exoplanet Survey Satellite (TESS) have generated large amounts of data in the form of photometric light curves and astronomical data [1], [2]. The current study introduces an explainable multi-modal deep learning framework named EXO-INSIGHT to improve exoplanet detection by analyzing temporal and spatial astronomical data. The framework analyzes the changes in the brightness of stars from light curve sequences using temporal learning models, whereas it also analyzes astronomical images to extract features using CNNs. The features from these two modalities are combined using a feature fusion mechanism to improve the reliability of the exoplanet detection process. Moreover, the framework also includes explainability techniques to highlight the relevant region of images and relevant segments of light curves to provide insights into the detection process [13]. The framework is implemented in the form of a web-based platform to provide researchers with a facility to upload their data and obtain results from the framework with explanations for the prediction results provided by the framework. The framework is expected to provide reliable results for analyzing large amounts of astronomical data for exoplanet detection.

Index Terms- Exoplanet detection, multi-modal deep learning, explainable artificial intelligence, astronomical data analysis, light curve analysis, convolutional neural networks, feature fusion, space telescope data.

I. INTRODUCTION

The exploration of planets beyond our solar system is one of the most important areas in modern astrophysics, and it is helping scientists understand the formation of planets and the possibility of life in other parts of the universe. In the past two decades,

space-based observing mission programs have significantly contributed to the development of this area of study. Programs like the Kepler Space Telescope and the Transiting Exoplanet Survey Satellite, or TESS, are continuously observing thousands of stars, generating extensive astronomical data sets. These data sets are generated by observing the change in the brightness of stars, along with images taken using sophisticated optical instruments. This has significantly expanded the possibilities for discovering new planetary systems.

One of the most frequently used techniques for detecting exoplanets is referred to as the transit detection method. Using this technique, scientists seek to detect slight changes in brightness of stars that are caused by exoplanets crossing in front of their respective stars and then in front of the observer. These slight changes in brightness are detected as periodic changes in the light curve signal, which provide details about exoplanets in terms of their size and other properties. However, these changes are very minute and may be subject to various kinds of disturbances or errors. Therefore, it is a very complicated task to detect transit signals in data sets [4], [5].

The rapid growth of astronomical data has encouraged the use of machine learning and deep learning methods for automated analysis. These computational approaches can learn complex patterns from large volumes of data and assist researchers in identifying potential exoplanet candidates.

Convolutional Neural Networks (CNNs) have proven effective in extracting spatial features from images, while sequential learning models such as Long Short-Term Memory (LSTM) networks can analyze time-

dependent patterns in stellar brightness data. By combining these techniques, automated systems can detect patterns that might be difficult to recognize through traditional analysis methods [4], [6], [7].

However, despite these advances, many detection systems that exist today utilize only a single type of observational data. A detection system that utilizes light curve analysis alone may not utilize the spatial information that is contained in the image data. In addition, deep learning methods have been criticized as being opaque and not explaining how they arrive at the prediction that they do. This can cause the level of confidence that the researcher has in the results that the detection system has generated to be reduced [13], [14].

To tackle this problem, this study introduces a new framework called "EXO-INSIGHT" based on the concept of "Explainable Multi-modal Deep Learning" to enhance the detection of exoplanets based on both temporal and spatial astronomical information. In this regard, the study combines photometric light curve information with astronomical images to identify new patterns, which might suggest the existence of exoplanets. This approach of utilizing various modalities of information helps improve the detection of exoplanets more accurately [2], [4], [6].

After the preprocessing stage, the system will then undergo analysis through two parallel pipelines. One pipeline is concerned with time series analysis based on the brightness of the stars, while the other deals with the analysis of the images captured in the search for spatial features. Through the two pipelines, the system is able to generate feature representations based on the analysis of the data provided. The feature fusion mechanism then enables the system to generate a prediction and a corresponding confidence level for the potential exoplanets [8], [11], [12].

II. EXOPLANET DETECTION AND ASTRONOMICAL DATA ECOSYSTEM

A. Photometric Light Curve Analysis

Photometric light curves are defined as the brightness of stars over a continuous period of time. When an exoplanet passes in front of its parent star from the

observer's point of view, there is a slight dimming effect observed in the star's brightness. This phenomenon is referred to as transit, and it gives us valuable information about the exoplanet's size and their periods of orbit. Light curve analysis is very vital in detecting exoplanet candidates. Advanced signal processing and machine learning are also used to analyze these signals and detect potential exoplanet transit events [4], [15].

In astronomical surveys involving large datasets, the light curve data is obtained through continuous observations of thousands of stars for long durations of time. This data is characterized by time series information that captures periodic as well as non-periodic changes in the brightness of the stars. Planetary transit is observed as short-duration changes in the brightness of the stars at regular intervals based on the orbital period of the planet. This requires effective preprocessing of the light curve data to normalize the data, remove noise from the observations, and split the data into effective time intervals. This reduces the impact of observation errors on the detection algorithm [4], [6].

In addition to vehicle-centric operations, IoT sensors also facilitate communication with external entities such as road-side infrastructure, traffic management systems, and cloud-based services. This connectivity allows vehicles to exchange data for traffic optimization, route planning, and cooperative driving. As a result, sensor data form the foundation of intelligent vehicular behavior, making their correctness and reliability critical for overall system safety [5].

B. Astronomical Imaging Data

Astronomical imaging provides spatial information about celestial objects and plays an important role in modern astrophysical observations. Telescopes equipped with advanced detectors capture high-resolution images of star systems, enabling researchers to study the spatial structure of stars and surrounding celestial bodies. These images allow scientists to observe brightness distributions, stellar formations, and other visual patterns that may indicate the presence of planetary bodies. When used together with photometric observations such as light curves, astronomical images provide

complementary information that improves the reliability of exoplanet detection systems [6], [7].

Astronomical images are commonly stored using specialized scientific formats such as the Flexible Image Transport System (FITS). This format is widely used in astronomy because it stores image data together with important metadata describing the observational conditions, telescope parameters, and celestial coordinates. Before these images are used for computational analysis, preprocessing steps are usually applied to enhance the quality of the data. These operations may include normalization of pixel intensities, removal of background noise, and enhancement of important visual features. Such preprocessing steps help reduce observational distortions and improve the accuracy of feature extraction methods used in automated detection systems [1], [6].

Deep learning techniques, particularly convolutional neural networks (CNNs), have become powerful tools for analyzing astronomical image datasets. CNN architectures automatically learn spatial features by applying convolution filters that detect patterns such as edges, textures, and brightness variations within images. In exoplanet detection systems, these models can analyze telescope observations or starshade images to identify spatial characteristics associated with potential planetary bodies. When combined with time-series analysis of light curves, image-based feature extraction contributes to a multi-modal detection framework capable of capturing both spatial and temporal patterns in astronomical data [7], [9].

C. Challenges in Exoplanet Detection

Although modern observation technologies have significantly improved the discovery of planetary systems beyond our solar system, several challenges still exist in detecting exoplanets accurately. Astronomical datasets often contain various types of noise introduced by instrumental limitations, environmental disturbances, and natural variability in stellar brightness. Stellar phenomena such as flares, pulsations, or star spots can create fluctuations in a star's observed brightness that closely resemble planetary transit signals. These variations can make it difficult to distinguish genuine planetary events from

natural stellar activity, thereby complicating the detection process [4], [16].

Another important challenge arises from the enormous volume of data generated by modern astronomical observation missions. Space telescopes and survey missions continuously monitor thousands of stars over long periods, producing extensive time-series datasets that must be processed and analyzed efficiently. The scale and complexity of this data make manual inspection impractical, requiring the use of automated computational techniques and intelligent algorithms to identify potential planetary signals within large observational datasets [2], [6].

False positive detections represent another major difficulty in exoplanet identification. Certain astrophysical events, such as eclipsing binary star systems or background stellar objects, can produce signals that closely resemble the transit patterns created by orbiting planets. As a result, detection systems must carefully analyze multiple sources of observational information to confirm the presence of a true exoplanet. Integrating different types of data, including photometric light curves and astronomical images, allows detection frameworks to distinguish genuine planetary signals from other astrophysical phenomena, thereby improving the reliability and accuracy of exoplanet detection methods [6], [7].

III. DEEP LEARNING AND EXPLAINABLE AI FOUNDATIONS

A. Convolutional Neural Networks for Image Analysis

Convolutional Neural Networks (CNNs) have become one of the most widely used deep learning models for image analysis tasks. These networks are designed to automatically learn spatial features from visual data by applying convolution filters across image pixels. Each convolution operation extracts local patterns such as edges, textures, and brightness variations, which are then combined across multiple layers to form higher-level representations of the input image. This hierarchical feature extraction capability makes CNNs highly suitable for analyzing complex image datasets in scientific applications, including astronomical observations [7], [9].

Astronomical imaging data often contain complex spatial information, including star clusters, brightness distributions, and background cosmic radiation. CNN models are effective in handling such data because they can automatically detect important spatial patterns without requiring manual feature engineering. During training, the network learns filters that respond to specific visual characteristics within the images. These learned features help distinguish between normal stellar observations and spatial structures that may indicate the presence of planetary bodies or other celestial phenomena [7], [8].

Pooling layers are typically incorporated within CNN architectures to reduce the dimensionality of feature maps while preserving important spatial information. By decreasing the spatial resolution of intermediate representations, pooling operations reduce computational complexity and help prevent overfitting. The extracted features are eventually passed through fully connected layers that perform classification tasks. In exoplanet detection systems, CNN-based image analysis enables the extraction of spatial features from astronomical images that contribute to identifying planetary candidates [8], [9].

B. Sequential Neural Networks for Time-Series Analysis

Time-series observations such as stellar brightness measurements require models capable of capturing temporal relationships between sequential data points. Sequential neural networks are specifically designed to process ordered datasets and learn dependencies across time steps. Among these models, Long Short-Term Memory (LSTM) networks have proven particularly effective for analyzing time-series signals due to their ability to retain information over long sequences [11].

LSTM networks contain memory cells that maintain information from previous observations and regulate data flow through specialized gating mechanisms. These gates control how information is stored, updated, or discarded within the network. Such architecture allows LSTM models to capture both short-term fluctuations and long-term patterns in sequential data. When applied to light curve analysis, LSTM models learn patterns associated with

periodic brightness dips that correspond to planetary transit events [6], [11].

Before training sequential models, light curve datasets are typically preprocessed and divided into smaller segments representing continuous time intervals. These sequences are used as inputs to the LSTM network, which analyzes variations in brightness across consecutive observations. Through training, the model becomes capable of distinguishing between transit patterns caused by exoplanets and irregular variations resulting from stellar activity or observational noise. This capability allows deep learning models to analyze large astronomical datasets efficiently and identify promising exoplanet candidates [4], [6].

IV. MULTI-MODAL DEEP LEARNING ARCHITECTURE

The architecture of the proposed EXO-INSIGHT framework is shown in Fig. 1. The system combines temporal analysis of photometric light curves with spatial analysis of astronomical images to improve the accuracy of exoplanet detection. By integrating information from these two observational modalities, the framework is able to capture complementary patterns that indicate potential planetary transit events.

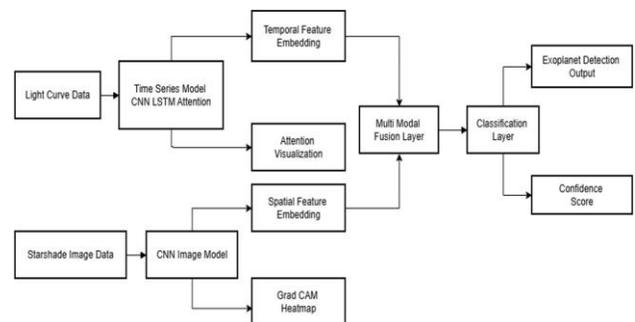


Fig. 1. Multi-modal deep learning architecture for exoplanet detection in the EXO-INSIGHT framework. (Internal Figure)

A. Light Curve Data Processing

The detection process begins with photometric light curve data representing variations in stellar brightness over time. These signals are processed using a time-series model that integrates

convolutional neural networks (CNN), long short-term memory (LSTM) networks, and an attention mechanism. The CNN layers capture local temporal patterns in the bright-ness signals, while the LSTM component models sequential dependencies across the observations.

B. Temporal Feature Embedding

The output of the time-series model is transformed into a temporal feature embedding that represents the important patterns extracted from the light curve signals. The attention mechanism also generates visualization outputs that highlight segments of the light curve that contribute significantly to the detection decision.

C. Astronomical Image Analysis

In parallel with the temporal pathway, starshade image data are processed using a convolutional neural network image model. The CNN extracts spatial features from the input images by detecting brightness distributions and structural patterns within the observed star systems.

D. Spatial Feature Embedding

The spatial features extracted from the CNN model are converted into spatial feature embeddings. These embeddings summarize the visual information contained in the astronomi-cal images. To improve interpretability, Grad-CAM heatmaps are generated to highlight image regions that influence the model's prediction.

E. Multi-Modal Feature Fusion

The temporal and spatial feature embeddings are combined through a multi-modal fusion layer. This stage integrates information from both data modalities and produces a unified feature representation of the observed system.

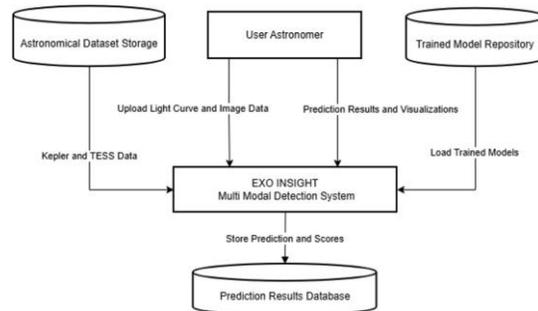
F. Classification and Detection Output

The fused feature representation is passed to a classification layer that produces the final prediction. The system determines whether the input observation corresponds to a potential exo-planet candidate and outputs a confidence score indicating the reliability of the prediction.

V. SYSTEM DATA FLOW

The operational workflow of the EXO-INSIGHT framework is illustrated in Fig. 2. The diagram describes how astronom-ical datasets move through the system from the user input stage to the final prediction output. The system processes both photometric light curve data and astronomical images through a sequence of processing stages that include data preparation, model inference, feature integration, and prediction generation.

Fig. 2. Data flow diagram illustrating the processing stages of the EXO-INSIGHT system. (Internal Figure)



A. Dataset Upload

The workflow begins when the user uploads observational datasets through the system interface. These datasets typically consist of light curve signals representing stellar brightness variations and astronomical images captured during telescope observations. Once the datasets are uploaded, they are stored temporarily for further processing.

B. Data Preprocessing



Before the data are analyzed by the deep learning models, preprocessing operations are applied to improve the quality of the observations. For light curve data, normalization and noise reduction

techniques are used to remove irregular variations. Astronomical images are also processed to enhance brightness information and remove noise artifacts.

C. Feature Extraction

After preprocessing, the datasets are forwarded to the deep learning models for feature extraction. The time-series model analyzes the light curve signals to identify temporal patterns associated with potential planetary transit events. At the same time, the convolutional neural network analyzes the astronomical images to extract spatial characteristics of the observed star systems.

D. Feature Integration

The features extracted from the temporal and spatial analysis pipelines are combined to form a unified feature representation. Integrating the two types of observations allows the system to capture complementary information that improves the reliability of the detection process.

E. Prediction Generation

The final stage of the workflow produces the prediction output of the system. The classification model analyzes the fused feature representation and determines whether the input observation corresponds to a potential exoplanet candidate. The system outputs the detection result together with a confidence score indicating the likelihood of the prediction.



VI. SYSTEM IMPLEMENTATION AND INTERFACE

The EXO-INSIGHT framework is implemented as a web-based application that enables users to upload astronomical datasets and perform automated

exoplanet detection using the proposed multi-modal deep learning model. The interface integrates data upload, model inference, and result visualization within a single interactive environment.

Fig. 3. EXO-INSIGHT system dashboard showing the entry interface for initiating the exoplanet detection process.

A. System Dashboard

The system dashboard serves as the main entry point of the application. It provides users with an overview of the system capabilities, including light curve analysis, CNN-based image processing, and fast inference features. Users can initiate the detection workflow by selecting the "Start Detection" option, which redirects them to the dataset upload interface.

B. Dataset Upload Interface

The dataset upload interface allows users to provide the required input data for the detection process. The system accepts two types of input: astronomical images used for spatial analysis and light curve data used for temporal analysis. Users can upload the files through drag-and-drop operations or by browsing local files. After uploading the datasets, the system forwards them to the preprocessing module for analysis.

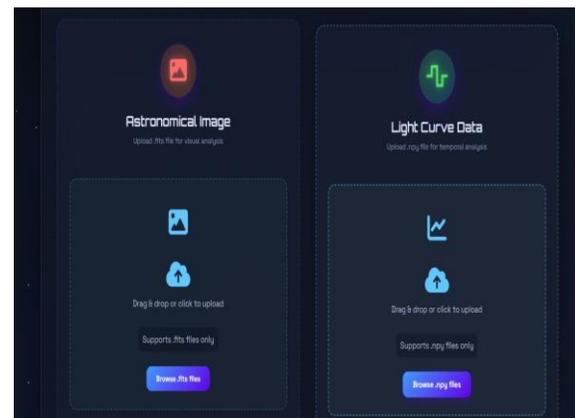


Fig. 4. Dataset upload interface allowing users to submit astronomical images and light curve data.

Fig. 5. Prediction results generated by the EXO-INSIGHT system showing fusion decision and confidence score.

C. Prediction Result Visualization

After the datasets are processed by the deep

learning models, the system generates prediction results that indicate whether a potential exoplanet signal is detected. The re-sults interface displays the fusion decision, confidence score, and model outputs from both temporal and spatial analysis pipelines. These visual outputs help users interpret the detec-tion results produced by the EXO-INSIGHT framework.

VI. DISCUSSION

The experimental implementation of the EXO-INSIGHT framework demonstrates the potential of multi-modal deep learning for analyzing astronomical observations. By combin-ing temporal analysis of photometric light curves with spatial feature extraction from astronomical images, the proposed approach is able to capture complementary information that may not be fully observable when using a single data modality. The integration of these two types of observations improves the reliability of identifying patterns associated with planetary transit events within large datasets [4], [6].

The architecture used in this work integrates convolutional neural networks for image analysis and sequential learning models for time-series processing. Convolutional networks are capable of extracting hierarchical spatial features from telescope images, while recurrent models such as LSTM net-works capture temporal dependencies in brightness variations observed in light curve signals [7], [11]. The combination of these models within a unified framework enables the system to analyze astronomical data more effectively by considering both spatial and temporal characteristics of the observed star systems.

Another important aspect of the proposed system is the inclusion of explainable artificial intelligence techniques. In many scientific applications, interpretability is essential for validating automated predictions. Visualization methods such as Grad-CAM highlight the image regions that influence the model's decision, while attention-based visualization identifies important segments within the light curve signals. These explanation mechanisms help researchers understand the pat-terns detected by the model and improve confidence in the automated

analysis process [13], [14].

The web-based implementation of the EXO-INSIGHT framework further enhances usability by providing an ac-cessible interface for uploading observational datasets and visualizing prediction results. Through this interface, users can submit astronomical image data and light curve signals, perform automated analysis, and observe detection results to-gether with confidence scores. Such an integrated environment supports efficient experimentation and facilitates interaction between astronomers and machine learning tools designed for large-scale astronomical data analysis.

VII. CONCLUSION AND FUTURE WORK

This work introduced EXO-INSIGHT, a multi-modal deep learning framework designed to support automated exoplanet detection from astronomical observations. The proposed sys-tem combines analysis of photometric light curve signals with spatial feature extraction from astronomical images. Temporal patterns within brightness variations are captured through se-quential learning models, while convolutional neural networks extract spatial representations from image data. By merging these complementary features through a fusion mechanism, the framework provides a more reliable approach for identifying potential planetary transit events within large astronomical datasets [4], [6].

The framework is implemented as a web-based application that allows users to upload observational datasets and obtain prediction results through an interactive interface. The system presents the detection decision together with a confidence score and visual explanations that highlight important regions within the input data. These interpretability features improve transparency and assist researchers in understanding the factors that influence the model's predictions [13], [14].

Future research can extend this work by incorporating larger datasets from recent astronomical missions such as Kepler and the Transiting Exoplanet Survey Satellite (TESS) [1], [2]. Additional improvements may include the use of advanced deep learning architectures and the

integration of other observational modalities to further enhance the accuracy and scalability of automated exoplanet detection systems.

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