Mesiri: Mephisto Early Supernovae Ia Rapid Identifier Postprint

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Abstract

The early time observations of Type Ia supernovae (SNe Ia) play a crucial role in investigating and resolving longstanding questions about progenitor stars and the explosion mechanisms of these events. Colors of supernovae (SNe) in the initial days after the explosion can help differentiate between different types of SNe. However, the use of true color information to identify SNe Ia at the early-time explosion is still in its infancy. The Multi-channel Photometric Survey Telescope (Mephisto) is a photometric survey telescope equipped with three CCD cameras, capable of simultaneously imaging the same patch of sky in three bands (u, g, i or v, r, z), yielding real-time colors of astronomical objects. In this paper, we introduce a new time-series classification tool named Mephisto Early Supernovae Ia Rapid Identifier (Mesiri), which, for the first time, utilizes real-time color information to distinguish early-time SNe Ia from core-collapse supernovae. Mesiri is based on the deep learning approach and can achieve an accuracy of 96.75% ± 0.79%, and AUC of 98.87% ± 0.53% in case of single epoch random observation before the peak brightness. These values reach towards perfectness if additional data points on several night observations are considered. The classification with real-time color significantly outperforms that with pseudo-color, especially at the early time, i.e., with only a few points of observations. The BiLSTM architecture shows the best performance compared to others that have been tested in this work.

Full Text

Preamble

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Mesiri: Mephisto Early Supernovae Ia Rapid Identifier

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Abstract

Early-time observations of Type Ia supernovae (SNe Ia) play a crucial role in investigating and resolving longstanding questions about progenitor stars and explosion mechanisms. The colors of supernovae in the initial days after explosion can help differentiate between different types of SNe. However, the use of true color information to identify SNe Ia at early times remains in its infancy. The Multi-channel Photometric Survey Telescope (Mephisto) is a photometric survey telescope equipped with three CCD cameras, capable of simultaneously imaging the same patch of sky in three bands (u, g, i or v, r, z), yielding real-time colors of astronomical objects. In this paper, we introduce a new time-series classification tool named Mephisto Early Supernovae Ia Rapid Identifier (Mesiri), which for the first time utilizes real-time color information to distinguish early-time SNe Ia from core-collapse supernovae. Mesiri is based on a deep learning approach and can achieve an accuracy of 96.75% $\pm$ 0.79% and an AUC of 98.87% $\pm$ 0.53% in the case of single-epoch random observation before peak brightness. These values approach perfection when additional data points from several nights of observations are considered. Classification with real-time color significantly outperforms that with pseudo-color, especially at early times when only a few observational points are available. The BiLSTM architecture shows the best performance compared to other architectures tested in this work.

Key words: techniques: photometric – telescopes – surveys

1. Introduction

The investigation of supernovae (SNe) is of paramount significance. As an illustration, Type Ia supernovae (SNe Ia), serving as standardized candles, provide a reliable means of measuring cosmic distances. They led to the discovery of the universe's accelerated expansion (Riess et al. 1998; Perlmutter et al. 1999) and also provide valuable constraints on the Hubble constant (e.g., Freedman et al. 2001; Shah et al. 2021). Obtaining early signals from SNe Ia explosions is crucial for various reasons. Radiative signals at early times can offer important constraints on explosion mechanisms, progenitor systems, and their physical origins (Kasen 2010; Nugent et al. 2011; Marion et al. 2016; Hosseinzadeh et al. 2017; Jiang et al. 2018; Dimitriadis et al. 2019; Bulla et al. 2020; Burke et al. 2021; Ashall et al. 2022; Sai et al. 2022). Moreover, variations in luminosity during this phase can reveal several aspects such as interactions with a companion star in a binary system, the surrounding envelope of the progenitor, or circumstellar material ejected by the progenitor before explosion (Meikle et al. 1996; Kasen 2010; Cao et al. 2015; Dimitriadis 2019; Shappee et al. 2019; Jiang et al. 2021). Following that, spectroscopic or photometric follow-up at early stages can also serve as a valuable benchmark for further observations at later epochs. The earlier an object can be classified, the more opportunities there are for the community to perform follow-up observations, and the more likely it is to bring about entirely new discoveries (Piro & Morozova 2016; Jiang et al. 2018; Stritzinger et al. 2018; Fausnaugh et al. 2021; Liu et al. 2024). Last but not least, in the initial days following an explosion, changes in color can reveal an asymmetric distribution of elements created through nucleosynthesis (Ni et al. 2022) and helium burning on the surface of a white dwarf (Jiang et al. 2017). The color evolution at early times can also be used to probe the location within the ejecta of ^{56}Ni and other radioactive isotopes (Dessart et al. 2014). Studies of early-time color curves of SNe Ia indicate that two branches may exist, i.e., the red and blue branches (Stritzinger et al. 2018; Bulla et al. 2020). This implies that using them as standard candles for cosmic distance measurements can introduce systematic errors, thus affecting the accuracy of cosmic distance measurements. Additionally, similar limitations exist in current SN explosion models and measurements of the Hubble constant (Shah et al. 2021, and references therein). Thus, precise and detailed identification of early-time SNe Ia is crucial and indispensable.

To address these challenges and further unravel mysteries of the universe, an increasing number of large-scale survey telescopes are currently in operation or planned, including the Vera C. Rubin Observatory Large Synoptic Survey Telescope (LSST; Ivezić et al. 2019), the Panoramic Survey Telescope and Rapid Response System (Pan-STARRS; Kaiser 2004; Flewelling et al. 2020), the Catalina Real-Time Transient Survey (CRTS; Drake et al. 2009), the Dark Energy Survey (DES; Abbott et al. 2018), the Asteroid Terrestrial-impact Last Alert System (ATLAS; Tonry et al. 2018), the Zwicky Transient Facility (ZTF; Bellm et al. 2019; Masci et al. 2019), the 2.5 m Wide Field Survey Telescope (WFST; Lou et al. 2016; Shi et al. 2018; Lou et al. 2020; Hu et al. 2022; Lei et al. 2022; Lin et al. 2022), and so forth. These ongoing and future surveys can generate enormous amounts of data and trigger millions of real-time alerts each night. This presents both unprecedented opportunities for studying transients and new challenges in efficiently processing and analyzing vast data sets.

SN observations can be accomplished through both spectroscopic and photometric techniques. Spectroscopic observations provide accurate constraints but require longer observation times and cannot be applied to SN searching in large-scale surveys. On the other hand, due to the high efficiency of photometric observations, more efforts have focused on early and rapid classification by photometric surveys. Various methods have been employed to analyze observational data, including visual inspection, spectroscopic analysis, and machine learning template matching, particularly deep learning-based methods (Huertas-Company & Lanusse 2023; Huertas-Company et al. 2023; Smith & Geach 2023). The color of celestial objects contains rich information and can be used for measurement of stellar atmospheric parameters and accurate flux calibration (Allende Prieto 2016). Poznanski et al. (2002) pointed out that based on $V - R$ and $R - I$ colors, SNe Ia with redshift less than 0.1 can be distinguished from other SNe. Thus, color and color evolution can provide valuable information about celestial objects.

In the investigation of early-time photometric classification of SNe, the Young Supernova Experiment (YSE; Jones et al. 2021) aims to obtain well-sampled Pan-STARRS g, r, i, z light curves of thousands of transient events, capable of discovering young transient events with a luminosity of about 21.5 mag. Charnock & Moss (2017) achieve high accuracy in classifying SNe using deep recurrent neural networks (DRNNs) with data including redshift before the night of the sixth observation with signal-to-noise ratio (SNR) > 4. RAPID (Muthukrina et al. 2019) uses DRNNs with gated recurrent units (GRUs) to automatically identify transient phenomena from the initial alert to the entire light curve by using PLAsTiCC. SuperNNova (Möller & de Boissière 2020) uses Bayesian neural networks and can incorporate additional information to improve early-time classification of SNe Ia and core-collapse supernovae (CCSNe), but requires between 2.4 ± 1.2 and 3.3 ± 1.4 photometric epochs on average to start accurately classifying SNe. Automatic Learning for the Rapid Classification of Events (ALeRCE; Carrasco-Davis et al. 2021; Förster et al. 2021; Sánchez-Sáez et al. 2021) is a broker system light curve classifier for processing the alert stream from ZTF by employing a balanced random forest method based on feature extraction. Qu & Sako (2022) proposed a photometric classifier, Supernova Classification with a Convolutional Neural Network (SCONE), based on a convolutional neural network (CNN) using wavelength-time heatmaps, achieving good classification results for early-time SN light curves. Fink (Leoni et al. 2022) utilizes feature extraction and active learning to identify early-stage SNe Ia.

Recurrent neural networks (RNNs) and their variants, including Long Short-Term Memory (LSTM; Hochreiter & Schmidhuber 1997), GRU (Cho et al. 2014; Chung et al. 2014), and Bidirectional Long Short-Term Memory (BiLSTM) networks, have been shown to be particularly powerful where sequential data are accompanied by a set of discrete labels (Charnock & Moss 2017; Caramete et al. 2020; Chaini & Kumar 2020; Dékány & Grebel 2020; Chatterjee et al. 2021; Čokina et al. 2021; Abduallah et al. 2022). However, until now, the overwhelming majority of previous work has focused on single-band light curves for SN classification. As illustrated here, only a few studies aim to promptly identify early-time SNe Ia after explosions. Multi-band simultaneous observational real-color information has not yet been explored for early-time classification.

This paper is organized as follows. A brief overview of the Multi-channel Photometric Survey Telescope (Mephisto) is provided in Section 2. We elaborate on our utilization of SNCosmo (Barbary et al. 2022) to simulate data in Section 3. The deep learning architectures based on RNNs, LSTM, GRU, and BiLSTM, as well as model assessment metrics, are outlined in Section 4. Our findings are presented in Section 5. Additional discussion is provided in Section 6. In Section 7, we encapsulate the culmination of our research findings. We implement a flat ΛCDM standard cosmology with $\Omega\Lambda = 0.7$, $\Omega M = 0.3$, $H_0 = 70.0$ km s^{-1} Mpc^{-1} in our simulations, and assume the comoving volumetric rate of SNe is 10^{-4} yr^{-1} Mpc^{-3} (Barbary et al. 2012).

2. Multi-channel Photometric Survey Telescope

Mephisto[3] (Yuan et al. 2020) is a wide-field telescope with a 1.6 m primary mirror located at the Lijiang Observatory in Lijiang City, Yunnan Province, China. It is equipped with three CCD cameras, each with a field of view of 2 square degrees, capable of simultaneously imaging the same patch of sky region in three different bands (u, g, i or v, r, z).

[Figure 1: see original paper] presents the transmission curves of the Mephisto u, v, g, r, i, z filters. For comparison, we also overplot the early spectra of one classical well-observed Type Ia case, SN 2011fe (Pereira et al. 2013). For the purpose of facilitating visual comparison, we have rescaled the spectra of the SN.

[3] http://www.mephisto.ynu.edu.cn/

Mephisto's survey mode, with sampling intervals ranging from days to minutes, allows for systematic searches and studies of various types of explosive events in the universe (e.g., Wang et al. 2024). In this work, we investigate the role of real-time color information in SN classification with an ideal case of 1 day cadence.

3. Simulation

With the objective of preparing the training sample, we simulate the photometric light curves of SNe for u, v, g, r, i, z filters of Mephisto using SNCosmo[4], a Python package for SN cosmology analysis. Different SN parameters in our simulation are adopted from the Open Supernova Catalog (OSC, Guillochon et al. 2017). The corresponding number of SNe in different classes (in column N), average peak magnitude (in column M_{peak}), and standard deviation of the peak magnitude (in column σ_M) are derived from all bands in OSC as mentioned in Table 1. The t_0 column expresses the average rise time[5], and we employ a Gaussian distribution across distinct categories. The models column indicates the number of built-in SN models in SNCosmo. The last column represents the overall number of samples for training, validation, and testing, which is obtained from simulations and subsequent filtering. The selection criteria are described later.

[4] https://sncosmo.readthedocs.io/en/stable/index.html

[5] All the rise times in this work refer to those in the rest frame.

For a typical SN Ia, the average rise time is about 20 days after explosion. However, in Yao et al. (2019), among a sample of 127 SNe, 50 are detected at least 14 days prior to the peak of the light curve, with a subset of 9 events being detected more than 17 days before the g-ZTF band peak. In Miller et al. (2020), the mean rise time of SNe Ia is estimated to be 18.9 days. Other rise times of SNe Ia have also been presented in other work (Firth et al. 2015; Branch & Wheeler 2017), which are between 17 and 20 days. Since our work focuses on early-time classification of SNe Ia, we only select samples with a minimum rise time of 17 days in the light curves after explosion for model training and testing.

We concentrate on SNe with a redshift range of [0, 0.1] owing to Mephisto's limiting magnitude. To generate redshift values for observed SNe, we utilize the built-in zdist function in SNCosmo. The resulting redshift distribution is illustrated in the left panel of [Figure 2: see original paper]. We perform further selection for different training subsamples. The right panel of [Figure 2: see original paper] shows the distribution for the sample containing three days of observations before the peak of the light curve. The redshift distribution of other subsamples does not show much difference.

SNCosmo offers a rich variety of SN models, including 15 submodels specifically for SNe Ia, such as the widely used SALT2 and SALT3 models. In this simulation, we adopt the parameters of SALT2 as the fundamental parameter settings for all other models. Additionally, as our emphasis lies in detecting early-time SN Ia explosions, the necessity for extended light curve observations post-peak luminosity is obviated. In addition to SNe Ia, we also incorporate other types of SNe provided by SNCosmo, including SNe Ib, Ic, Ib/c, Ic-BL, IIP, IIL, IIb, and IIn. By including these diverse SN models, the simulated light curves of SNe within the same class become more varied. The number of submodels corresponding to each SN type is listed in the models column of Table 1.

For SNe Ia, we adopt hsiao (Hsiao et al. 2007), hsiao-subsampled (Hsiao et al. 2007), salt2 (Guy et al. 2007; Ellis et al. 2008; Guy et al. 2010; Betoule et al. 2014; Taylor et al. 2021), salt2-extended (Hounsell et al. 2018; Pierel et al. 2018), salt3 (Kenworthy et al. 2021), salt2-extended-h17 (Hounsell et al. 2018), nugent-sn91bg (Nugent et al. 2002), and mlcs2k2 (Jha et al. 2007) models.

After obtaining the simulated flux of the celestial object, we utilize Equation (1) for conversion of flux to magnitude:

$$m = -2.5 \log_{10}(\text{flux}) + 25.0,$$

where it is assumed that the zero-point is 25.0, the default value built into SNCosmo.

Based on pilot observations and weather monitoring at Lijiang Observatory (GMG; Xin et al. 2020), we simulate measurement errors in SN light curves. The SNR is calculated by Equation (2):

$$\mathrm{SNR} = \frac{n_{\mathrm{target}}}{\sqrt{n_{\mathrm{target}} + n_{\mathrm{skybright}} + n_{\mathrm{readout}} + n_{\mathrm{dark}}}},$$

where n_{target} represents target flux, $n_{\mathrm{skybright}}$ is sky background noise flux, n_{readout} represents readout noise flux, and n_{dark} is dark current noise flux. The 5σ limiting magnitudes of a 20 s exposure in six filters of Mephisto are 20.07, 20.23, 21.09, 21.22, 20.91, and 19.51, respectively.

To establish a comparatively realistic and comprehensive sample for training and testing purposes, we apply the following selection criteria:

1. Observations with low SNR (<5) or below the 5σ limiting magnitude are dropped.
2. At least 17 days of observations before the g-band peak of the light curve.
3. Historical observational data statistics reveal that SNe Ia account for approximately 25% of the total SNe from OSC (Guillochon et al. 2017). Thus, we construct our simulation sample with the same ratio, i.e., the number of SNe Ia to CCSNe is approximately 1:3.

After applying these selections, a total of 8561 samples of simulated effective light curves are available, including 2141 SNe Ia samples and 6420 CCSNe samples (Table 1). Examples of simulated light curves and color light curves can be seen in Figures 3 and 4[6], respectively. Here, we define "Days after the trigger" as the days with continuous following observations since the first detection of a Mephisto transient finder trigger.

[6] We select samples based on whether any one of u, g, i bands meets the criteria, then pad the missing data as inputs for the model. Figure 4 shows the color evolution obtained from the original photometric data, resulting in some missing data points (e.g., the second panel from the top in the right column in Figure 4) in the color plot. Such scenarios do indeed occur.

Dust in the Milky Way and host galaxy affects the shape of an observed SN spectrum. It is important to take these effects into account in our model when fitting the model to observed data for more realistic situations. Consequently, we utilize the built-in SN models and dust parameters in SNCosmo for dust extinction and reddening, including dust extinction in the host galaxy and the Milky Way. We add both host galaxy dust and Milky Way dust. Dust propagation effects are referenced from Fitzpatrick (1999), and host effects and dust in the Milky Way are referenced from Barbary et al. (2012). Another assumption that we must make clear is that host galaxy effects are not taken into account when identifying SNe Ia in this study.

4. Deep Learning Architectures and Evaluation Metrics

4.1. RNN, LSTM, GRU and BiLSTM

In time-series data classification, RNNs such as LSTM, GRU, and BiLSTM demonstrate superior performance and are widely applied. With the aim of selecting the optimal method for identifying early-time SNe Ia, in this work we train several DRNNs to classify light curves of SNe Ia from CCSNe and name our approach Mephisto Early Supernovae Ia Rapid Identifier (Mesiri). The training procedures and parameters of Mesiri are shown in [Figure 5: see original paper].

The DRNN models a function that maps an input multi-band light curve matrix, $I_{s,t}$, for transient s up to a discrete time t onto output probabilities over classes $\{c = 0, 1, 2\}$[7], and prediction error. Among them, the first six quantities represent the magnitude and magnitude error corresponding to u, g, i bands, while the following six quantities represent the true color information and associated color information errors. Here, true color refers to color information obtained through simultaneous observations in multiple bands, as opposed to color information obtained through non-simultaneous multi-band observations. The output $y_{s,t}$ is a probability vector with length 3, where each element $y^c_{s,t}$ is the model's predicted probability of each class c, such that $\sum_c y^c_{s,t} = 1$.

[7] In RNN classification, an additional category is typically added to the output classes, often referred to as the "unknown" or "other" category. The purpose of this additional category is to handle samples that the model cannot accurately classify into known categories, namely those that do not belong to any known category in the training set. This approach helps the model better deal with unknown samples, thereby improving the model's generalization ability and accuracy in classifying unknown samples.

From Figure 3, it is evident that in certain filters we have limited data as a result of fluctuations in the throughput efficiency of different bands. To align data points simultaneously observed with different filters, we utilize Gaussian Process (GP) for interpolation (Demianenko et al. 2023). We perform interpolation based on time points, i.e., starting from the earliest observed point and ending with the latest one. In most cases, the earliest data appear in the g or r bands since they have relatively high efficiency. For example, if observations in the u, g, i filters show that the g-band has 60 observation points ([0, 59]), while the observation time range for the u-band is [5, 35], we interpolate values in the [0, 4] and [36, 59] intervals using GP. The same interpolation technique is applied to other bands. Moreover, there is a possibility that no observation data are available for a particular filter. In such cases, we adopt the commonly used padding technique in neural networks to fill in values with a padding value of -1.

The interpolated images before and after interpolation are displayed in the left and middle panels of [Figure 6: see original paper], respectively, and the right panel shows the corresponding color light curves. The embedded subplot in the upper left corner of the right panel represents the color evolution in the first 17 days. Finally, the Mesiri pipeline is illustrated in [Figure 7: see original paper].

We define the global objective function as:

$$f(I;\theta) = \log \frac{1}{N} \sum_{i=1}^{N} L_i,$$

where θ stands for the parameters (e.g., weights and biases of the neurons) of our DRNN architecture. We define the input $I_{s,t}$ as a $t \times 12$ (or $t \times 12+1$, when redshift is considered) matrix representing the light curve up to a time step t, where 12 represents input features including $u_{s,t}$, $g_{s,t}$, $i_{s,t}$, $u_{s,t}$ error, $g_{s,t}$ error, $i_{s,t}$ error, $(u-g)_{s,t}$, $(u-i)_{s,t}$, $(g-i)_{s,t}$, $(u-g)_{s,t}$ error, $(u-i)_{s,t}$ error, $(g-i)_{s,t}$ error.

We sum the weighted categorical cross-entropy over all t time steps in the training set, such that y assumes the binary label $\{0,1\}$, and $p(y)$ is the probability that the output belongs to y. We expect $p(y)$ to be as large as possible when $y=1$. Looking at the ideal case: when y is a positive case, $p(y)=1$, and the loss is 0; conversely, when $p(y)$ tends to 0, $\log(p(y))$ tends to negative infinity, leading to a very large loss. We describe the architecture in detail as follows:

Input. The input is a $t \times 12$ matrix, or $t \times 12 + 1$ when redshift is considered. However, as we are implementing a sequence classifier, we can consider the input at each time step as being a vector of length $t \times 12$. Here input features include six magnitude items: $u_{s,t}$, $g_{s,t}$, $i_{s,t}$, $u_{s,t}$ error, $g_{s,t}$ error, $i_{s,t}$ error, and six color items: $(u-g)_{s,t}$, $(g-i)_{s,t}$, $(u-i)_{s,t}$, $(u-g)_{s,t}$ error, $(g-i)_{s,t}$ error, $(u-i)_{s,t}$ error, corresponding to the abbreviations in [Figure 7: see original paper].

First Layer. We apply all RNN/LSTM/GRU/BiLSTM unit cells in this study, as they offer significantly shorter training times without deterioration in classification performance. They can capture dependencies in time-varying data by controlling the information remembered at each step of the light curve. In the initial layer, each input sequence is encoded into a higher-dimensional representation one time step at a time, utilizing 256 units to generate an output vector of dimension $t \times 256$.

Second Layer. The second RNN/LSTM/GRU/BiLSTM layer is conditioned on the input sequence. It takes the output of the first layer and generates an output sequence. We set up this layer with 128 units, with dropout and recurrent dropout layers to maintain the $t \times 128$ output shape.

Third Layer. The third RNN/LSTM/GRU/BiLSTM layer is conditioned on the second sequence. It takes the output of the second layer and generates an output sequence. Again, we establish this layer with 64 units, with a dropout layer to maintain the $t \times 64$ output shape.

Dense Layer. In neural networks, a dense layer is the fundamental and simplest type of layer, often known as a fully connected layer. It establishes a connection between all 64 neurons from the previous layer with 3 neurons in the output layer by employing Equation (5). In classification problems, the output vector includes both SN categories.

Neurons. The output of each neuron in a neural network layer can be formulated as the weighted sum of connections to it from the preceding layer:

$$y_i = \sum_{j=1}^{M} W_{ij} x_j + b_i,$$

where x_j are the different inputs to each neuron from the previous layer, W_{ij} are the weights of the corresponding inputs, b_i is a bias that shifts the threshold where inputs become significant, j is an integer running from 1 to the number of connected neurons in the previous layer (M), and i is an integer running from 1 to the number of neurons in the next layer. For the dense layer, $\mathbf{x}$ is simply the (1×64) matrix from the output of the second layer, $\mathbf{y}$ comprises the three output classes, j runs from 1 to 3, and i runs across the 64 input neurons from the last layer.

Dropout. We implement dropout regularization in each layer of the neural network to reduce overfitting during training. This is an important step that effectively ignores randomly selected neurons during training, such that their contribution to the network is temporarily removed. This process causes other neurons to more robustly handle the representation required to make predictions for the missing neurons, making the network less sensitive to the specific weights of any individual neuron. We set the dropout rate to 20% of the neurons present in the previous layer each time the dropout block appears in the DRNN in [Figure 5: see original paper].

Recurrent Dropout. Just as with regular dropout, recurrent dropout has a regularizing effect and can prevent overfitting. We set the recurrent dropout rate to 20% of the neurons present in the previous layer each time the dropout block appears in the DRNN in [Figure 5: see original paper].

Activation Function. Each neuron in a neural network applies an activation function to introduce nonlinearity, which enables the network to handle a wide range of data. The most commonly used activation function for feed-forward networks is the hyperbolic tangent function, commonly abbreviated as tanh.

Sigmoid Regression. The sigmoid regression activation function is utilized in the final layer, specifically to handle binary classes. This function is applied to the dense layer output of each time step, normalizing the output vector between 0 and 1. Consequently, the sum of values across all classes in each time step generates a total value of 1. This process enables the output to be interpreted as a proportional likelihood that the input SN at each time step belongs to a certain class. The resulting vector of probabilities is generated through this procedure. The sigmoid function is computed with a sigmoid activation function defined as:

$$\text{sigmoid}(x) = \frac{1}{1+e^{-x}}.$$

We utilize the output sigmoid probabilities to prioritize the most fitting SN classes for each SN light curve at each time step.

4.2. Evaluation

In evaluating performance, we utilize five commonly used metrics to assess Mesiri. The most straightforward metric is accuracy, defined by Equation (8), which refers to the proportion of correctly classified SNe in each class relative to the total number of SNe in each class. Precision, also known as purity, is the ratio of true positive predictions to the total number of positive predictions for each class, defined by Equation (9). Recall, also known as completeness, is similar to the true positive rate. It measures the number of correct predictions in each class compared to the total number of that class in the testing set and is defined by Equation (10). The F1 score is the harmonic mean of precision and recall, combining their trade-offs as defined by Equation (11). It ranges from 0 to 1, with higher values indicating better model performance. The F1 score can be used as a comprehensive evaluation metric for classification model performance. The AUC represents the area under the Receiver Operating Characteristic (ROC) curve, which measures the accuracy of a binary classification model's predictions. AUC ranges from 0 to 1, with higher values indicating better model performance. By observing AUC, we can also understand the model's performance at different thresholds, helping us choose the optimal classification threshold. These metrics help evaluate classification model performance and measure their accuracy, coverage, and stability from different perspectives. Apart from the aforementioned evaluation metrics, the confusion matrix is a common approach to visualize classification model performance, defined as in Table 2.

The evaluation metrics are formally defined as:

$$\text{Accuracy} = \frac{\text{TP}+\text{TN}}{\text{TP}+\text{TN}+\text{FP}+\text{FN}},$$

$$\text{Precision (Purity)} = \frac{\text{TP}}{\text{TP}+\text{FP}},$$

$$\text{Recall (Completeness)} = \frac{\text{TP}}{\text{TP}+\text{FN}},$$

$$\text{F1 score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}.$$

Here TP, TN, FP, and FN represent the number of true positive samples, true negative samples, false positive samples, and false negative samples, respectively.

5. Result

The variation of light curves in the Mephisto u, v, g, r, i, z bands is attributed to transmission efficiency. Therefore, we employ GP and padding interpolation to process the original light curve data, ensuring uniform light curve length across each band. During model training, we divide the data into training, validation, and testing sets. To enhance the objectivity of performance evaluation and mitigate the risk of overfitting, we employ a five-fold cross-validation approach where model training is repeated five times, and each time the testing set is selected differently from the simulation sample. Multiple models are trained using distinct sets of simulated data points at early stages of SN explosion, e.g., different numbers of data points before the peak. This allows us to achieve a diverse set of models tailored to specific data scenarios for improved classification matching.

The experimental results, shown in [Figure 8: see original paper] and Table 3, present the accuracy of identifying early-time SNe Ia under different redshift information. We emphasize that since the uncertainties associated with each evaluation are derived from the standard deviation computed from five-fold cross-validation, some of these values (see Table 3 and Appendix A) may exceed 100% after incorporating the standard deviation. A similar scenario is also depicted in Section 6 from Figures 9 to 15. The first column in Table 3 represents the neural network base cell units utilized in Mesiri, while the subsequent time column signifies the observational epochs of pre-maximum luminosity. Most results show acceptable performance, e.g., accuracy greater than 96%, and our models based on BiLSTM are not only lightweight but also highly accurate. Notably, the identification accuracy of SNe Ia from a light curve when first discovered/triggered without redshift is 97.15% $\pm$ 0.63%. Further details can be found in Section 6.1. Detailed identification results for each scenario can be found in Appendix A and Table A1. Furthermore, Appendix C and Figure C present all confusion matrices. We also adopt a normalized version of the confusion matrix for easier interpretation.

The increasing accumulation of observational data demonstrates that classification accuracy with simultaneous observation of three bands with color features is comparable to that of non-simultaneous observation of three bands with color features. This observation underscores the positive impact of increased observational data on classification accuracy. Through tests conducted on a Windows 11 operating system with an Intel® Core™ i7-10700 CPU @ 2.90 GHz processor running a classifier in Jupyter Notebook, testing was performed on 31 epochs of 5 observed target sources. The average time to classify each instance was approximately within 2 s. It is relevant to mention that our network architecture is implemented using TensorFlow (Abadi et al. 2016) and Keras (Chollet et al. 2015). The entire pipeline is implemented using the Python programming language and scikit-learn (Pedregosa et al. 2011).

6. Further Comparison

Given that our findings indicate the superior performance of the network architecture utilizing BiLSTM, all subsequent analyses focus on the BiLSTM model.

6.1. Early Observation and Training Sample

In the following, we describe the "very early" and "early" observation scenarios in the context of the training sample. The "very early" observation scenario is considered as observation at a very early time (just after explosion/discovery) with good cadence. For instance, if a source has observational data from Mephisto for 17 days before peak brightness across all three bands, then "very early time" is taken as [1, 2, 3, 4, 5, …, 17] sequentially. The second scenario (i.e., "early") means our observations are comparatively not so early, and data acquisition is random before maximum luminosity (e.g., 3, 7, 10, 15, …, days after explosion/discovery).

In [Figure 9: see original paper], we compare the accuracy of early and very early time classification models. The blue triangle line represents results of an early SN explosion with random epochs of observation, while the light blue shaded region represents the standard deviation of model errors after five-fold cross-validation. Conversely, the green cross line and green shaded region represent results of early explosion using sequential epochs of observation. Upon examining the results, it is evident that the two trained models produce nearly similar outcomes. Here, it should be noted that the identification accuracy, precision, and AUC of "very early" SNe Ia, when first discovered/triggered without redshift, are 97.15% $\pm$ 0.63%, 92.86% $\pm$ 4.10%, and 98.5% $\pm$ 0.75%, respectively.

6.2. With Redshift versus Without Redshift

Lochner et al. (2016) and de Soto et al. (2024) observe that redshift is not notably influential in SN classification at low redshifts, whereas Qu & Sako (2022) demonstrates that inclusion of redshift information enhances performance at all epochs. Spectroscopic redshift is time-consuming and difficult to obtain at early stages. In reality, using deep learning for photometric redshift is an active area of research (e.g., Brescia et al. 2021; Zhou et al. 2022). Therefore, we implement a comparative analysis to assess the impact of redshift. The backbone architecture is diagrammed in [Figure 10: see original paper], which is similar to Mesiri, with the only difference being the addition of redshift information between the third and fourth layers. [Figure 11: see original paper] demonstrates that our constructed classification model remains insensitive to the inclusion of redshift information during the initial phase of SN explosion. With redshift information, the variation of the estimate (i.e., the shaded region) shrinks slightly.

6.3. Simultaneous versus Non-simultaneous Observations

To differentiate Mephisto's performance from other telescopes under conditions of non-simultaneous observation data, we process the simulated data to obtain approximately non-simultaneous observation data. We then implement a comparative analysis using BiLSTM. It should be emphasized that these data are still based on Mephisto's observation scheme. Specifically, the data were processed as follows: first, early-time data of the u, g, i bands were randomly selected for multiple observations. For example, to study classification with three observations, we randomly select three observations before peak luminosity in the u-band, and similarly for the g and i bands. The selected u, g, i data would be aligned. It is important to note that this alignment does not refer to aligning data in the time domain. Subsequently, the color information and corresponding color error information are calculated. Nevertheless, here the color information is not the true color obtained through simultaneous observations. Finally, the selected data are inserted into the model for training.

In [Figure 12: see original paper], one can see that our network demonstrates good performance in SN classification, e.g., the AUC reaches nearly 100% after three days of observation. In almost all cases, simultaneous observation outperforms non-simultaneous observation, especially when only a few days of observations are available. With sufficient accumulated data, Mesiri achieves similarly high performance in early-time identification of SNe Ia in both simultaneous and non-simultaneous observation scenarios.

6.4. With Color versus Without Color

We emphasize that each additional computation incurs a time cost, even in the present era with remarkable computing capabilities. To assess the model's capacity to deduce color information, we undertook a test to determine if explicitly incorporating color information into the data improved model performance.

The experimental results from [Figure 13: see original paper] demonstrate that the accuracy of observed data explicitly containing color information exceeds 96%. Starting from the accumulation of second observation data, the identification accuracy of SNe Ia surpasses 98%, as depicted by the solid lines in the light blue triangle region of [Figure 13: see original paper]. Conversely, observed data without explicit color information exhibit lower accuracy, below 94% for the majority of early-time SN eruptions, shown by the dashed lines in the light green region of [Figure 13: see original paper]. Consequently, it can be inferred that the accuracy of observed data explicitly containing color information significantly surpasses accuracy achieved when color information is not explicitly displayed. It is worth noting that even without explicitly displayed color information, combined observations of the u, g, i bands using our

BiLSTM-based model architecture result in SNe Ia identification accuracy that is still above 89.55% ± 0.59%. This accuracy surpasses precision attained in existing research on early-time identification of SNe Ia.

6.5. u, g, i versus v, r, z

On account of Mephisto's scheduled survey mode, which is divided into filter combinations of u, g, i and v, r, z, this section examines the efficacy of identifying SNe Ia in the early stages of their explosion under the v, r, z filter combination mode. We selected the BiLSTM method, which demonstrated the best comprehensive evaluation among the above methods, as the final basic unit method to compare the performance of SNe Ia identification in the u, g, i and v, r, z bands. The comparative evaluation criteria employ the same metrics as for u, g, i, specifically encompassing accuracy, precision, recall, AUC, and F1 score. Since these five metrics yield comparable findings, only the accuracy comparison is displayed in [Figure 14: see original paper]. The classification accuracy shown in [Figure 14: see original paper] indicates that the u, g, i filters yield slightly better accuracy than the v, r, z filters when observed data span one or two days. In this regard, we compare early-time spectral data of SNe Ia and CCSNe by selecting and combining them with the Mephisto total efficiency curve. We found that the variation of emission and absorption lines in the u, g, i bands during SNe Ia explosions is much larger than that of CCSNe during early-time explosion. Furthermore, the variations of emission and absorption lines in the u, g, i bands during early-time SNe Ia explosions are stronger than those in the v, r, z bands. Despite this, both the u, g, i and v, r, z-based methods achieve accuracy better than 94% in early-time identification of SNe Ia.

6.6. Shallow Learning

Gagliano et al. (2023) achieve comparable or superior results to leading classification algorithms with a simpler network architecture using photometric redshift, extinction, and host galaxy photometry (shallow learning), attaining an overall accuracy of 82% ± 2% and accuracy of 87% ± 5% at both early (within 3 days of an event's discovery) and late phases (within 30 days of discovery). We also construct a shallow learning architecture with only a light curve with true color information, by way of contrast, as diagrammed in the left panel of [Figure 15: see original paper]. It consists of a single BiLSTM layer of 64 units. The right panel in [Figure 15: see original paper] compares accuracy between Mesiri and shallower learning. Upon scrutiny, it becomes evident that despite its reduced computational time, the shallow learning model does not demonstrate the same level of effectiveness as Mesiri.

7. Summary

Mephisto has established itself as a powerful facility for time-domain astronomy owing to its capacity to capture the real-time color of various celestial objects, including transients. The real-time color of an SN explosion can provide vital information about progenitor stars and explosion mechanisms, especially during the early phase. Real-time color with better accuracy can be used for early classification of transients such as various types of SNe or tidal disruption events (TDEs), or similar objects. We take advantage of simultaneous three-band photometry by Mephisto and study classification between SNe Ia and CCSNe. We developed an identifier, Mesiri, based on an RNN. The training samples are simulated according to Mephisto's observing features (see simultaneous multi-band observations), the weather conditions at its location, and 1 day cadence observational mode data. We focus on both real-time and non-real-time observational data with random cadence. The identifier Mesiri can efficiently identify early observed SNe Ia with accuracy, precision, and AUC above 96%. Moreover, accuracy, precision, and AUC reached 96.75%, 98.42%, and 98.87%, respectively, when real-time data were considered (i.e., once we had single-epoch observational data). Specifically, the identification accuracy, precision, and AUC of SNe Ia at first discovery/trigger without redshift are 97.15% $\pm$ 0.63%, 92.86% $\pm$ 4.10%, and 98.5% $\pm$ 0.75%, respectively. Our results have better significance than previous studies of a similar kind and emphasize the crucial information provided by true color. The key points of our study are summarized below:

1. Classification utilizing true color demonstrates superior performance compared to that employing pseudo-color, particularly during initial phases characterized by limited observations.

2. In this study, several neural networks are compared, including RNN, LSTM, GRU, and BiLSTM. Our results show that BiLSTM performs best in early classification of SN Ia explosions with true color information. Therefore, BiLSTM has been employed in successive evaluations (see Section 6).

3. Mesiri remains insensitive to the inclusion of redshift for low-redshift SNe.

4. Our calculations indicate that although identification accuracy of SNe Ia is higher (96%) when explicit color information (i.e., $(u-g)$, $(g-i)$, $(u-i)$, $(u-g)_{\mathrm{error}}$, $(g-i)_{\mathrm{error}}$, $(u-i)_{\mathrm{error}}$) is utilized, if we only use three bands and their corresponding errors (i.e., u, g, i, u_{error}, g_{error}, i_{error}), the identification accuracy is good enough (90%) but consumes less computation time.

5. The u, g, i filters yield slightly better accuracy than the v, r, z filters when observed data span one or two days. Nevertheless, both the u, g, i and v, r, z-based cases achieve accuracy better than 94% in early-time identification of SNe Ia.

Additionally, one major source of contamination is extinction and reddening from the Milky Way and the host galaxy. We perform extra comparisons with test samples including extinction (Ohlson et al. 2024). By applying the Mesiri classifier to light curves with extinctions, we observed that identification accuracy decreases to 88% on average. Such effects will be incorporated in our future study.

Moreover, it is noteworthy that the training sample employed in our study was not subjected to data balancing, resulting in an imbalanced sample ratio between SNe Ia and CCSNe during model training. Despite this, our model can achieve unprecedented performance with true color information. However, we acknowledge the following limitations in our study. First, we carry out our research using simulated data, which cannot reflect real observational noise or other systematics. A larger training sample with real observations, especially data from the target telescope (i.e., Mephisto), is required. Second, studies of SNe Ia have revealed their inherent diversity, which was not taken into account in our simulated data. The classification of subtypes of CCSNe as well as other transients, such as TDEs and kilonovae, will be included in our classification scheme using true color information in future studies. It is worth noting that Mephisto is presently in the commissioning phase and is already providing good scientific data (e.g., Chen et al. 2024a, 2024b; Yang et al. 2024).

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Appendix A. Mesiri Early Classification Evaluations

In Section 5, to concisely present experimental findings, we selected evaluation results for five scenarios of Mesiri as listed in Table 3. Here, we enumerate all scenario evaluation results obtained from our experiments. Table A1 presents an elaborate account of diverse evaluation metrics following five-fold cross-validation on SNe Ia using BiLSTM units, taking into account the quantity of observed data from the commencement of SN explosion.

Table A1. Utilizing Mesiri for Early-time Identification of SNe Ia Across All Scenarios in the Initial Stages of SN Explosions

ObsDay(s)	Accuracy	Precision	Recall	F1 score	AUC
1	96.75% ± 0.79%	98.42% ± 0.95%	67.9% ± 7.93%	80.08% ± 6.07%	98.87% ± 0.53%
2	99.07% ± 0.18%	99.3% ± 0.56%	91.23% ± 1.81%	95.08% ± 0.99%	99.92% ± 0.02%
3	99.48% ± 0.24%	99.56% ± 0.53%	95.3% ± 2.64%	97.36% ± 1.26%	99.98% ± 0.00%
...	...	...	...	...	...

Note: Note that each evaluation, when combined with uncertainties represented by standard deviations, may exceed 100%.

Appendix B. Sample Distribution

Given our assumption in sample selection that the rise time to peak luminosity of SN explosion is 17 days, practical observational constraints often prevent availability of complete observational data. To simulate realistic scenarios, each scenario assumes a different duration of observational data. Consequently, we employed a scenario-specific model training approach to better illustrate sample distribution for pre-maximum epochs during the model training process. Figures B1, B2, and B3 depict sample distribution for pre-maximum epochs in each scenario (pre-maximum epochs are provided in the title description of each subplot).

[FIGURE:B1] The sample distribution for the pre-maximum epochs in each scenario (the pre-maximum epochs are provided in the title description of each subplot).

[FIGURE:B2] Continued from B1, the sample distribution for the pre-maximum epochs in each scenario (the pre-maximum epochs are provided in the title description of each subplot).

[FIGURE:B3] Continued from B2, the sample distribution for the pre-maximum epochs in each scenario (the pre-maximum epochs are provided in the title description of each subplot).

Appendix C. Confusion Matrix

As highlighted in Section 4.2, in addition to the five metrics for model evaluation provided after model training in the main text, the confusion matrix is also a commonly used evaluation metric. We employed Mesiri for each scenario-specific training sample, as illustrated by the distribution of sample pre-maximum luminosity in Appendix B, and the corresponding confusion matrices for each scenario are provided. Figures C1 and C2 represent confusion matrices. From left to right and top to bottom, each subplot represents the confusion matrix of the corresponding samples (left panel) and its normalized version in percentages (right panel) for the pre-maximum epoch of observations, respectively. Beneath each set of confusion matrices, descriptions are provided for the sampled scenarios that align with model training.

[FIGURE:C1] Confusion matrices, from left to right and top to bottom, each subplot represents the confusion matrix of the corresponding samples (left) and normalized confusion matrix (right) for the pre-maximum epoch of observations, respectively.

[FIGURE:C2] Continued from C1, from left to right and top to bottom, each subplot represents the confusion matrix of the corresponding samples (left) and normalized confusion matrix (right) for the pre-maximum epoch of observations, respectively.

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Note: Figure translations are in progress. See original paper for figures.