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Review

Review of 2D Spectral Image Processing Techniques

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Abstract

The processing of two-dimensional (2D) spectral images constitutes a critical and multifaceted discipline in contemporary astronomical data analysis. As spectroscopic instruments evolve towards higher multiplexing, resolution, and sensitivity, the raw 2D data captured by detectors present increasingly complex challenges that transcend simple one-dimensional extraction. This review provides a systematic and comprehensive examination of the methodological evolution in this field over the past two decades. It gathered relevant studies by searching mainstream academic repositories and general search engines with the core keyword '2D Spectral Image', and selected qualified references according to accessibility and research relevance. We categorize the landscape into three major paradigms: (1) physics-based modeling and algorithmic correction techniques for geometric distortion, scattered light, and sky background; (2) data-driven machine learning and deep learning approaches for image correction, spectral classification, and faint signal detection; and (3) the development of open-source software pipelines that democratize advanced processing. A central contribution of this review is a detailed comparative analysis of the performance metrics, underlying assumptions, and practical limitations of prominent algorithms. We highlight the transformative impact of convolutional neural networks (CNNs) and vision transformers (ViTs) on tasks such as celestial object classification and exoplanet detection, while also acknowledging the enduring importance of robust physical models for calibration and uncertainty quantification. The discussion culminates in an assessment of persistent challenges—including computational scalability, model generalizability, and interpretability—and outlines promising future directions at the intersection of AI, statistical inference, and large-scale survey science.

Keywords: 2D spectroscopy; spectral extraction; scattered light removal; sky background subtraction; machine learning; convolutional neural networks; deconvolution; LAMOST; pipeline software

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1. Introduction

Modern astronomical spectrographs, whether large ground-based facilities like the Large Sky Area Multi-Object Fiber Spectroscopic Telescope (LAMOST) or space-borne instruments like the Hubble Space Telescope's Imaging Spectrograph (STIS), do not directly produce clean, one-dimensional flux-versus-wavelength plots commonly adopted in astrophysical journals. Instead, they produce complex 2D images recorded by charge-coupled device (CCD) or CMOS detectors. In these images, the spectral information of potentially thousands of celestial objects is encoded alongside complex overlapping instrumental and environmental artifacts [1,2].

The core challenge of 2D spectral processing is to invert a complex, non-linear transformation. The detected signal at each pixel, $D(x, y)$, can be conceptually modeled as

$$D(x,y) = [S(\lambda) * PSF(x,y,\lambda)] \cdot F(x,y) + B_{sky}(x,y,t) + B_{scat}(x,y) + N \quad (1)$$

where $S(\lambda)$ is the true source spectrum, PSF is the wavelength-dependent point-spread function (incorporating optical aberrations, fiber profile, and diffraction effects); $F(x, y)$ is the flat-field response; B_{sky} is the time-varying sky background; B_{scat} is the scattered light component, and N denotes position-dependent stochastic detector noise, following a combination of Poisson photon noise and Gaussian readout noise. The PSF itself is often not static; it can vary with field position, wavelength, and even time due to mechanical flexure or thermal changes [3].

Traditional 'optimal extraction' algorithms, which gained prominence in the 1980s and 1990s, operate under the simplifying assumption that the spectrum is perfectly aligned along detector columns and that the PSF is separable and constant across the slit or fiber [3,4]. As Kelson (2003) rigorously demonstrated, these 1D methods become suboptimal and can introduce significant systematic errors when the slit image is tilted, curved, or distorted—conditions that are the norm rather than the exception in wide-field, multi-object spectrographs [3,5]. The degradation in signal-to-noise ratio (SNR) and photometric accuracy for misaligned spectra provided a compelling impetus for the development of full 2D processing frameworks.

The massive datasets generated by large-scale spectroscopic surveys (like SDSS, GAIA, DESI, RAVE, HERMUS, 4MOST, etc.) have further accelerated innovation. LAMOST, for instance, routinely acquires 4000 spectra in a single exposure, necessitating automated, robust, and computationally efficient pipelines that can handle crowded fields, varying seeing conditions, and complex cross-talk between adjacent fibers [1,6]. This review charts the journey from early 2D correction algorithms to the current era of AI-powered analysis, providing a detailed taxonomy of techniques and a critical evaluation of their capabilities.

For this systematic review, we restricted the literature search to publications published between 2005 and 2025, covering the two-decade development of 2D spectral image processing as described above. We adopted a hybrid retrieval strategy combining professional astronomical databases, general academic platforms and public search engines. All searches were performed within the title, abstract and keyword (TI/AB/KW) fields instead of full text, to balance retrieval accuracy and efficiency.

The core search term was 2D Spectral Image. We enabled the built-in synonym expansion function of ADS by default, and adopted the unified Boolean query across all platforms:

("2D Spectral Image" OR "Two-dimensional Spectral Image") AND (spectral extraction OR sky subtraction OR scattered light removal OR astronomical pipeline)

To cover subdomains including long-slit spectral reduction and Integral Field Unit (IFU) processing, we further added two groups of complementary queries: *long-slit spectral reduction AND 2D correction* and *IFU data processing AND spectral image*.

The initial number of records retrieved from each resource is listed as follows: ADS (1127), Web of Science (983), AMiner (746), Bing and Baidu (329). The total number of initially retrieved literature was 3185.

Cross-database duplicate records were removed via a two-step procedure: we first used reference management software to automatically match paper titles, authors and publication years for preliminary deduplication; ambiguous duplicates were further verified and eliminated manually by comparing full contents. A total of 642 duplicate entries were removed in this step.

We formulated explicit inclusion and exclusion criteria for subsequent screening.

Inclusion criteria: (1) Peer-reviewed journal articles, conference papers and doctoral dissertations focusing on 2D astronomical spectral image processing; (2) Studies targeting spectral data from mainstream telescopes, including LAMOST and Hubble STIS; (3) Original algorithm research, methodological improvement or comparative analysis of processing pipelines.

Exclusion criteria: (1) Pure review papers without independent methodological research; (2) Studies only focusing on one-dimensional spectral processing; (3) Non-English literature and works irrelevant to astronomical spectral imaging.

After deduplication and preliminary screening based on the above rules, 276 candidate papers remained. We prioritized studies with landmark methodological innovations, high academic influence, and high relevance to the three major technical paradigms of this review. Finally, 30 representative landmark studies were selected for in-depth sorting and systematic analysis.

It should be noted that we prioritized literature with publicly available full texts during screening for the convenience of content collation and verification. This strategy may introduce selection bias, as some high-quality studies without accessible full texts might be omitted. To mitigate this issue, we supplemented several high-impact papers (only abstract available) into the reference list for auxiliary reference.

The entire literature collection and screening workflow follows the PRISMA 2020 reporting guidelines (Akhmetali et al., 2025; Sangvikar et al., 2025) [7,8].

2. Physics-Based Modeling and Algorithmic Correction Techniques

This section delves into the foundational algorithms that address specific physical artifacts in 2D spectral data. These methods are typically derived from first principles of optics and detector physics, offering high interpretability and reliability when their underlying assumptions are met.

2.1. Advanced Fiber Spectrum Extraction and Geometric Rectification

The accurate extraction of individual spectra from a dense fiber array like LAMOST's requires moving beyond simple aperture photometry. Early work focused on characterizing the fiber profile and cross-talk [6,9]. A significant advancement was the shift towards model-fitting approaches. The 2-D Exponential Polynomial Model proposed by Zhang et al. (2012) fits the spatial profile of each fiber trace across the dispersion direction using a flexible functional form [10]. This method explicitly accounts for the profile's variation with wavelength and fiber position, leading to more accurate flux measurements, especially for faint targets where the profile wings contribute a larger fraction of the total signal.

An alternative, powerful framework is provided by deconvolution-based extraction. The algorithm developed by Li et al. (2015) formulates the extraction as an inverse problem: given the observed 2D image, solve for both the 1D spectrum and the 2D PSF simultaneously [11]. This iterative, practical deconvolution computation is particularly effective in handling overlapping fiber profiles and complex background structures. Its performance was benchmarked in a subsequent comparative study, which found it to offer superior resilience to noise compared to direct profile-fitting methods under certain conditions [12].

Pushing the autonomy further, the Blind Deconvolution method introduced by Yin et al. (2017) relaxes the requirement for a predefined or parameterized PSF model [13]. By leveraging certain statistical priors and iterative refinement, this technique can recover both the spectrum and the PSF directly from the data, making it highly adaptable to different instrumental configurations or unexpected optical behaviors. However, this flexibility can come at the cost of increased computational demand and potential convergence issues.

Geometric distortions, such as the 'smile' effect (wavelength-dependent curvature of spectral lines), must also be corrected to ensure accurate wavelength calibration. The Curve Distance Method proposed by Zheng et al. (2019) provides a targeted solution for this by modeling and rectifying the bending in 2D fiber spectra, thereby directly enhancing the precision of radial velocity measurements [14].

2.2. Modeling and Removing Scattered Light Contamination

In high-resolution echelle spectrographs, light scattered from the grating grooves and optical surfaces can contaminate inter-order regions and even leak into adjacent orders, creating a low-level, structured background. This is especially problematic for faint spectral features and in the ultraviolet. The seminal 2D Scattered Light Removal Algorithm for STIS data, described by Valenti et al. (2002) [2], demonstrated that a 1D treatment is fundamentally inadequate. Their model incorporates multiple physical components: echelle grating scatter, detector halo, telescope PSF wings, and ghost images. The algorithm iteratively constructs a model of the scattered light by using a preliminary extracted spectrum as the source, then subtracts this model from the original 2D image. This process, which is more physically motivated than simple background interpolation, is crucial for accurate analysis of deep absorption lines and faint emission features.

Beyond its substantial improvement in physical accuracy, the algorithm also imposes considerable computational and memory overhead, as quantitatively documented in [2]. Benchmarked on a typical early-2000s workstation, a 360 MHz Sun Ultra 60 with 256 MB physical memory, the 2D iterative scattered light removal implementation consumed 8.1 min of CPU time per spectral Imset (from Figure 17 in [2]). Supporting multiple wavelength-dependent convolution kernels increased the executable size to 270 MB, easily exceeding available physical memory and triggering performance-degrading disk swapping. Even two decades ago, this physically comprehensive 2D correction approach already involved intensive iterative fitting, multi-kernel convolution, and substantial memory occupation. These historic runtime and hardware requirements establish a clear quantitative baseline, demonstrating that traditional physics-based 2D artifact correction is inherently computationally expensive. This further underscores the computational scalability challenge highlighted in later sections and motivates the adoption of GPU acceleration and optimized parallel pipelines for modern large-scale spectral survey data processing.

2.3. Sophisticated Sky Background Subtraction and Flat-Fielding

For ground-based observatories, the time-varying and spatially non-uniform sky emission (from airglow, scattered moonlight, and light pollution) is a dominant source of contamination. Traditional methods that subtract a constant or linearly interpolated background from each column often fail in crowded fields or near bright sky lines. The 2D Sky-Background Modeling Algorithm for LAMOST, developed by Zhu & Ye (2012), represents a major step forward [15]. It constructs a smooth 2D model of the sky emission across the entire focal plane by selectively using pixels identified as pure sky, providing a more accurate subtraction than column-by-column approaches.

This concept was later refined using machine learning principles. Wu et al. (2018) proposed an Improved KICA-based 2D Sky Model [16]. By employing an enhanced Kernel Independent Component Analysis technique, their method can better separate the celestial signal from the sky background in the presence of complex, non-linear correlations, further reducing residual sky contamination in the extracted spectra.

Furthermore, the FLAME pipeline (Belli et al., 2018) [17] developed for multi-slit optical and near-infrared spectrographs achieves precise geometric rectification and optimized sky subtraction via coupled 2D polynomial spatial–spectral transformation, supporting data processing for Keck LRIS and LBT LUCI instruments with a flexible modularized architecture. To improve sky background separation without supplementary offset sky frames, Non-negative Matrix Factorization (NMF) has been extended into full 2D spectral modeling, outperforming traditional PCA-based decomposition by producing roughly tenfold more valid eigenspectra; this strategy has been well validated on Keck ESI, Magellan MagE, and VLT X-Shooter echelle slit data (Kolganov et al., 2025) [18]. Meanwhile, newly released open-source pipelines continuously advance end-to-end 2D calibration: Excalibuhr implements dedicated order tracing, nodding-based sky removal and standardized flat correction tailored for high-resolution VLT/CRIRES+ echelle spectra (Zhang et al., 2025) [19], while CARRSSPipeline introduces nonlinear spectral reprojection and empirical flux calibration specially designed for multi-object spectra from SALT-RSS spectrograph, resolving complicated flat-field inhomogeneity induced by uneven primary mirror illumination (Kharchilava et al., 2025) [20]. Moreover, cross-platform benchmark research between PypeIt and spec2D based on Keck DEIMOS datasets quantitatively reveals evident performance gaps in sky subtraction accuracy and artifact elimination, providing practical references for optimizing subsequent 2D correction parameter configuration across different reduction frameworks (Garg et al., 2024) [21].

Flat-fielding, the correction of pixel-to-pixel sensitivity variations, is a prerequisite for precise photometry. The Spectroflat library, introduced by Hoelken et al. (2024), offers a generic, 2D-aware solution for spectro-polarimetric data [22]. It goes beyond simple division by a lamp flat by modeling the flat-field response as a function of both pixel position and instrument configuration (e.g., grating angle, polarization state), ensuring consistent normalization critical for measuring small polarization signals.

A summary can be seen in Table 1.

Table 1. Summary of physics-based 2D spectral processing methods.

Category	Algorithm/Method	Core Idea	Main Advantage	Limitation/Note
Spectrum extraction	2D exponential polynomial model [10]	Fits spatial profile along dispersion	More accurate flux for faint targets	Requires predefined functional form
	Deconvolution extraction [11]	Inverse problem: solve for spectrum and PSF simultaneously	Handles overlapping profiles/complex background	Iterative, computationally intensive
	Blind deconvolution [13]	No predefined PSF; recovers from data statistically	Highly adaptable (no prior PSF needed)	High cost, potential convergence issues
	Curve distance method [14]	Models & corrects wavelength-dependent curvature	Improves radial velocity precision	Targets specific geometric distortion
Scattered light	STIS 2D algorithm [2]	Iterative scatter model using preliminary spectrum	Physically motivated (critical for deep lines)	Historically high CPU/memory cost

Table 1. *Cont.*

Category	Algorithm/Method	Core Idea	Main Advantage	Limitation/Note
Sky subtraction	2D sky modeling [15,21]	Smooth 2D model using pure-sky pixels	Better than column-by-column interpolation	Requires reliable sky pixel identification
	Improved KICA [16]	Enhanced kernel independent component analysis	Handles non-linear correlations, lower residuals	Less interpretable than linear methods
	NMF full 2D modeling [18]	Non-negative matrix factorization extended to 2D	~10× more valid eigenspectra	Recent; needs validation on more datasets
	FLAME, Excalibuhr, CARRSSPipeline, etc. [17,19,20]	Modular, end-to-end 2D calibration pipelines	Integrated corrections, telescope-specific	Dependent on instrument mode
Flat-fielding	Spectroflat library [22]	Flat response as function of pixel & instrument state	Essential for small polarization signals	Designed for spectro-polarimetric data

3. The Data-Driven Revolution: Machine Learning and Deep Learning

The last decade has witnessed the rise of a complementary paradigm: using data-driven models to learn the complex mappings and patterns within 2D spectral data directly. These methods often excel at tasks that are difficult to model analytically or require high-level pattern recognition (Table 2).

Table 2. Summary of machine-learning and statistical approaches for 2D spectral data.

Category	Algorithm/Method	Core Idea	Main Advantage	Limitation/Note
ML for image correction	ML-based Multifibre Image Correction (Xu+ 2020) [23]	Image-to-image translation using supervised learning	Effective for irregular/non-linear artifacts	Requires high-quality ground-truth labels
	CNNs/U-nets for cosmic ray rejection	Learn spatial hierarchies, morphology, and context	Excellent at distinguishing cosmic rays from emission lines	Needs large labeled training sets
	VAEs/GANs for inpainting & augmentation	Generate realistic synthetic 2D spectra, fill missing data	Useful when complete physical model is unavailable	Generation may introduce artifacts
Deep learning for classification	DRC-net (Zhang+ 2023) [24]	Deep residual convolutional network for 2D spectra	High accuracy (stars/ galaxies/quasars)	Performance depends on training label quality
	Multimodal Classification Network [25]	Fuses 2D spectra + photometric images via separate CNN branches	Leverages complementary information for ambiguous objects	Requires both spectral and imaging data
	TDSC-net (attention mechanism) [26]	Dynamic spatial-spectral attention weighting	Interpretable, mimics expert focus on lines	Attention adds computational complexity
	ViT for spectroscopy (Moraes+ 2026) [27]	Adapts vision transformer to 2D-formatted spectra	Outperforms SVM/RF; comparable to AstroCLIP	Performance validated only on surveyed data scope

Table 2. *Cont.*

Category	Algorithm/Method	Core Idea	Main Advantage	Limitation/Note
AI for homogenization & faint signal	SpectroTranslator (for stellar parameters) [28]	Learns to translate parameters between surveys	Enables reliable cross-survey catalog homogenization	Requires overlapping observations for training
	MLCCS (Garvin+ 2024) [29]	CNN on cross-correlated data cubes for exoplanets	Detects lower-contrast planets than traditional CCF	Specialized for high-contrast spectroscopy
Uncertainty quantification	2D Gaussian Process framework (Fortune + 2024) [30]	Models wavelength-and-time-correlated noise (GP with separable kernel)	Principled uncertainty estimates for atmospheric parameters	Computationally intensive; kernel selection matters
	Bayesian inference (MCMC nested sampling)	Full posterior distributions from hierarchical models	Properly propagates covariance from 2D extraction	Computationally expensive; requires careful prior specification

3.1. Machine Learning for Image Correction and Processing

The application of machine learning (ML) to 2D spectral image correction represents a paradigm shift from purely physics-driven models to data-driven, adaptive solutions. Traditional correction algorithms rely on explicit analytical models for artifacts like cosmic ray hits, bad pixel clusters, and fiber cross-talk. While effective for well-characterized systematics, these models often struggle with non-linear, spatially variable, or instrument-specific defects that are difficult to parameterize. ML, particularly supervised learning, offers a powerful alternative by learning the complex mapping between corrupted and clean images directly from large volumes of observational and simulated data. The work by Xu et al. (2020) on ML-based Multifibre Image Correction demonstrated this potential [23]. Their approach treated the correction task as an image-to-image translation problem. They trained a model (e.g., a Random Forest or a shallow neural network) on pairs of real LAMOST 2D spectral images and their corresponding 'ground truth' corrected versions, which were often painstakingly produced by expert manual intervention or via sophisticated physical simulation. The model learned to predict corrections for defects such as localized intensity fluctuations, edge distortions from optical vignetting, and pattern noise from detector readout, achieving correction fidelity that matched or exceeded traditional methods for certain artifact classes, especially those with irregular patterns.

The success of such ML correction hinges on several key factors: the quality and representativeness of the training dataset, the choice of feature representation, and the design of the loss function. A common approach is to extract small patches from the 2D image and use pixel intensities within a local neighborhood as features. The model is trained to minimize a loss function such as the Mean Squared Error (MSE) or a perceptual loss that compares high-level features:

$$L(\theta) = \frac{1}{N}\sum_{i=1}^{N}\left\| f_\theta\left(I_i^{\text{corrupt}}\right) - I_i^{\text{clean}}\right\|^2 \tag{2}$$

where f_θ is the ML model with parameters θ, I_i^{corrupt} is the input corrupted image patch, and I_i^{clean} is the target clean patch. More advanced architectures, such as Convolutional Neural Networks (CNNs) and U-Nets, have since been adopted for this task. These deep learning models can capture spatial hierarchies and contextual information across the entire image, making them exceptionally good at tasks like cosmic ray rejection, where the model must distinguish between sharp, high-energy particle strikes and genuine astrophysical emission lines based on their morphology and surrounding context.

Beyond basic correction, ML is being used for more sophisticated preprocessing steps. For instance, generative models like Variational Autoencoders (VAEs) or Generative Adversarial Networks (GANs) can be trained to 'inpaint' missing data in corrupted spectral regions or to generate realistic synthetic 2D spectra for data augmentation. Furthermore, unsupervised or self-supervised learning techniques are being explored to identify and characterize novel types of systematic errors without requiring manually labeled clean data, by learning the underlying distribution of 'normal' spectroscopic data. These data-driven methods are particularly valuable for new instruments where a complete physical error model is not yet available, allowing for rapid pipeline development and robust data quality assurance even in the early phases of a survey.

Nevertheless, this label generation scheme has inherent limitations. Ground-truth labels obtained via manual expert intervention are susceptible to systematic observer biases arising from subjective experience and individual judgment. Meanwhile, labels derived from physical simulations rely on simplified physical assumptions and may fail to fully reproduce the complex characteristics of real observed spectra. When the machine learning model is trained on millions of 2D multifibre spectral images with such biased labels, these hidden biases will be encoded into the model parameters. In large-scale spectral processing tasks, the propagated biases are extremely difficult to detect and may eventually cause unquantified deviations in spectral correction, calibration and subsequent scientific analysis.

3.2. Deep Learning for Spectral Classification and Feature Extraction

The advent of deep learning, particularly CNNs, has revolutionized the classification of celestial objects using their 2D spectra. These networks learn hierarchical features directly from the image pixels. The DRC-Net (Deep Residual Convolutional Network) method, presented by Zhang et al. (2023), was specifically designed for this purpose, achieving high accuracy in classifying stars, galaxies, and quasars based solely on their 2D spectral images [24].

Recognizing that spectra are often accompanied by imaging data, the Multimodal Classification Network developed by the same group fuses information from 2D spectra and broad-band photometric images [25]. This architecture uses separate CNN branches to extract features from each modality before combining them in a fusion network. This approach leverages complementary information—the detailed chemical and velocity information from spectra with the morphological and color information from images—leading to more robust and accurate classifications, especially for ambiguous objects.

Further architectural innovations include attention mechanisms. The TDSC-Net (Two-Dimensional Spectral Classification Network) incorporates attention modules that allow the network to dynamically weight the importance of different spatial regions and spectral channels in the 2D image [26]. This 'learning to look' capability mimics how an expert astronomer might focus on specific spectral lines, improving classification performance and offering a degree of interpretability.

The most recent advance involves ViTs. As explored by Moraes et al. (2026) [27], pre-trained ViT architectures designed for natural image processing can be adapted for spectroscopic analysis after converting 1D spectra into 2D image-formatted inputs. The model captures both local spectral line features and global correlations across the whole spectral field via self-attention mechanisms. Fine-tuned on massive SDSS and LAMOST spectral datasets pre-converted to 2D images, the ViT implementation was benchmarked against traditional machine learning and existing deep learning alternatives: its classification accuracy outperforms classical algorithms, including Support Vector Machines and Random Forests, and delivers comparable prediction precision to the spectrum encoder of AstroCLIP on classification and redshift estimation tasks. While competitive against these selected baseline models across the tested datasets, its performance superiority is only validated within the surveyed data scope rather than across all published spectral classification frameworks. This work marks an early practical attempt at ViT adoption for large-scale real astronomical spectroscopic data without dependence on fully synthetic training samples.

Despite the outstanding classification accuracy achieved by CNN, attention-based TDSC-Net and ViT architectures on benchmark datasets, deep learning models for 2D spectral classification suffer from multiple practical drawbacks rarely addressed above. First, the classification performance heavily hinges on the quality and coverage of labeled training data; model accuracy declines sharply when test samples contain uncommon celestial types absent from training sets. Second, these networks are prone to overfitting under limited labeled spectral data, resulting in excellent in-sample classification results but degraded performance on real observational data with unmodeled instrumental artifacts or unusual noise patterns. In terms of cross-instrument transferability, models trained exclusively on LAMOST 2D spectra usually cannot be directly applied to spectral data acquired by telescopes with disparate dispersion, pixel sampling and optical distortion features without extra domain adaptation and parameter fine-tuning. In practical astronomical surveys, such deep learning classifiers also frequently produce misclassification failure cases for faint-source spectra with extremely low signal-to-noise ratios, where heavy background noise distorts intrinsic spectral morphological features and confuses the feature extraction modules of neural networks.

3.3. AI for Data Homogenization and Faint Signal Detection

Machine learning is also proving invaluable for ensuring consistency across heterogeneous datasets and for detecting signals buried in noise. The SpectroTranslator deep neural network addresses the critical issue of systematic offsets between different spectroscopic surveys [28]. Trained on stars observed by multiple surveys, it learns to translate stellar parameters (like effective temperature, surface gravity, and metallicity) from one system to another, effectively homogenizing large catalogs and enabling reliable population studies.

Perhaps one of the most dramatic demonstrations of AI's potential is in the detection of exoplanets via high-contrast spectroscopy. The MLCCS (Machine Learning for Cross-Correlation Spectroscopy) method, developed by Garvin et al. (2024), uses a CNN to analyze cross-correlated spectral data cubes [29]. Instead of relying on a simple peak in the cross-correlation function (CCF), the CNN is trained to recognize the subtle, Doppler-shifted pattern of molecular absorption lines (e.g., from water or methane) that is the signature of an orbiting planet. This approach can detect planets with significantly lower contrast ratios than traditional CCF SNR metrics, potentially revealing a new population of fainter companions.

3.4. Advanced Statistical Modeling for Uncertainty Quantification

Accurate uncertainty quantification is as critical as the measurement itself, especially when deriving precise astrophysical parameters from 2D spectra. Traditional error propagation often assumes pixel noise is independent and identically distributed (i.i.d.), an assumption frequently violated in spectroscopic data due to correlated noise structures. These correlations arise from both instrumental effects (e.g., charge diffusion in CCDs and inter-pixel capacitance) and astrophysical/data reduction origins (e.g., residual fringing and imperfect sky subtraction that leaves correlated residuals). Ignoring these correlations can lead to significant underestimation of parameter uncertainties and, consequently, overly confident but potentially biased scientific conclusions. The work by Fortune et al. (2024)

directly addresses this by introducing a 2D Gaussian Process (GP) Framework for modeling noise correlated in both the wavelength and time dimensions in exoplanet transmission spectroscopy [30]. Their model treats the noise in a 2D data array (wavelength vs. time) as a draw from a GP with a covariance kernel K that factorizes into separate wavelength and time components:

$$K\big((\lambda, t), (\lambda', t')\big) = k_\lambda(\lambda, \lambda') \cdot k_t(t, t') + \sigma_n^2 \delta_{(\lambda,t),(\lambda',t')} \tag{3}$$

where k_λ and k_t are kernel functions (e.g., Matérn and squared exponential) modeling correlations along the spectral and temporal axes, respectively, and σ_n^2 represents white noise. This framework allows for a principled and flexible separation of the planetary absorption signal from the correlated stellar and systematic noise, leading to more reliable uncertainty estimates on atmospheric parameters like chemical abundances and temperature-pressure profiles.

This Gaussian regression framework can be applied to realize wavelength calibration and noise modeling directly on CCD-acquired 2D long-slit spectral images, matching the core scope of 2D spectral data reduction in this review.

The adoption of such advanced statistical models is part of a broader trend towards Bayesian inference in spectroscopic analysis. Beyond GPs, hierarchical Bayesian models are being used to simultaneously fit populations of stars or galaxies while accounting for individual measurement uncertainties and shared hyperparameters. Markov Chain Monte Carlo (MCMC) and nested sampling techniques are routinely employed to explore high-dimensional parameter spaces and obtain full posterior probability distributions for derived quantities, rather than just point estimates and Gaussian errors. For example, when fitting stellar atmospheric models to an extracted 1D spectrum (which itself comes from a 2D image), a proper Bayesian pipeline would propagate the covariance matrix from the 2D extraction step into the likelihood function for the spectral fit. This ensures that correlations between adjacent wavelength bins in the extracted spectrum—arising from the PSF and extraction process—are correctly accounted for, preventing spurious claims of detection for weak spectral features.

The move towards these sophisticated statistical tools is essential for frontier science, such as detecting biosignatures in exoplanet atmospheres or measuring subtle cosmological parameters from large spectroscopic surveys, where controlling systematic errors at the sub-percent level is paramount.

4. Software Tools and Pipelines: Enabling Community Adoption

The transition from research algorithms to robust, user-friendly software is a critical step in advancing the field. Open-source pipelines and libraries democratize access to state-of-the-art methods, ensure reproducibility, and foster community standards. These tools vary in scope from specialized libraries for a single task to comprehensive frameworks for end-to-end data reduction.

For educational purposes and processing of data from smaller telescopes, PyLongslit provides an accessible entry point [31]. Implemented in Python, it offers a transparent, scriptable workflow for the classic steps of long-slit spectroscopy reduction: bias/dark subtraction, flat-fielding, wavelength calibration, sky subtraction, and spectral extraction. Its design philosophy emphasizes clarity and user control, making it an excellent tool for students and researchers to understand the fundamental transformations applied to their data. While it may not incorporate the latest 2D deconvolution or ML techniques, its modularity allows users to replace standard steps with more advanced algorithms as needed.

For specialized calibration needs, particularly in high-precision spectro-polarimetry, the Spectroflat library stands out [17]. Spectro-polarimetric data requires exceptionally accurate flat-fielding to measure tiny polarization signals (often <0.1%). Spectroflat addresses this by providing a generic, instrument-agnostic framework for modeling the 2D response of a spectro-polarimeter. It goes beyond a simple division by a lamp flat by constructing a pixel-by-pixel sensitivity model that can depend on various parameters like wavelength, polarization state, and grating angle. This library encapsulates best practices and physical models into a reusable package, significantly reducing the risk of calibration-induced systematic errors in sensitive measurements.

At the scale of major surveys, integrated pipelines are essential (as shown in Table 3). The LAMOST 2D Pipeline is a prime example, incorporating many of the algorithms discussed in this review into an automated, production-grade system [1,6]. It handles the entire workflow from raw CCD frames to calibrated 1D spectra for thousands of fibers per exposure. Its architecture typically includes modules for: (1) pre-processing (bias, dark, flat); (2) fiber location and tracing using model fits or image analysis; (3) scattered light and sky background modeling using 2D algorithms; (4) optimal extraction using profile-fitting or deconvolution methods; and (5) wavelength calibration and flux standardization. Such pipelines are engineered for reliability, throughput, and maintainability, often featuring extensive logging, quality assurance (QA) plots, and database integration for tracking millions of spectra.

Table 3. Comparison of Representative 2D Spectral Processing Software.

Software/Tool	Primary Purpose	Key Features	Language/ Platform	Reference/ Resource
PyLongslit v1.1.5	Educational/manual long-slit reduction	Simple, transparent workflow; excellent for learning basics	Python	[31]
Spectroflat	Spectro-polarimetric flat-fielding	Generic, physical model-based; high precision for polarization	Python	[17]
LAMOST 2D Pipeline	Production reduction of multifibre spectra	Automated, high-throughput; integrates advanced 2D algorithms	C/Python	[1,6]
IRAF/ twodspec	General spectroscopic reduction (legacy)	Extensive suite of tasks; historical standard	IRAF (C)	NOAO IRAF [1]
Astropy/ specutils	Spectrum manipulation and analysis	Modern Python ecosystem; interoperability with other Astropy tools	Python	Astropy Project [2]
PypeIt v1.0.3	Automated reduction in slit spectra	High automation; supports many optical/IR instruments	Python	[32]

[1] https://iraf.readthedocs.io/en/latest/tasks/noao/index.html. [2] https://www.astropy.org/. All of the above versions are accessed on 6 June 2026.

Typical detector-induced artifacts dominating raw 2D spectral data quality include hot/dead bad pixels, fringe interference, and residual non-uniform flat-field response. Such instrumental defects heavily affect subsequent flux calibration and spectral extraction, and most preprocessing pipelines are designed specifically to suppress these detector-originated systematic errors.

The ecosystem is further enriched by libraries within broader astronomical software suites. The Astropy project's specutils package provides core data structures for 1D spectra and tools for their manipulation, which are often the final product of 2D processing pipelines. The trend is clearly towards modular, open-source, Python-based tools that leverage a rich ecosystem of scientific computing libraries (NumPy, SciPy, scikit-learn, and TensorFlow/PyTorch for ML). This environment facilitates the integration of new ML models or statistical methods into existing pipelines, accelerating the adoption of cutting-edge research by the broader community. The use of version control (e.g., Git), continuous integration, and containerization (e.g., Docker) is also becoming standard, ensuring software reliability and reproducibility across different computing environments.

5. Performance Comparison and Trends

A qualitative (as shown in Table 4) and quantitative (as shown in Table 5) comparison of the discussed methods reveals clear trends in the evolution of 2D spectral processing. The following analysis synthesizes findings from the reviewed literature.

Table 4. Comparative Analysis of Spectral Extraction Methods.

Method Category	Key Technique	Reported Advantage /Limitation	Typical Context
Model Fitting	2-D Exponential Polynomial Model [10]	Accurate flux for variable PSF; requires good profile model.	LAMOST fiber spectra
Inverse Problem	Practical Deconvolution Algorithm [11]	Handles overlapping profiles & complex background; computationally intensive.	Crowded fiber fields
Blind Inference	Blind Deconvolution [13]	No prior PSF model needed; convergence and uniqueness challenges.	Adaptive/ unknown instrument response
Geometric Correction	Curve Distance Method [14]	Effective for smile distortion correction; specific to curvature artifact.	Wavelength calibration refinement

Table 5. Performance of Deep Learning Classification Models.

Model Architecture	Key Innovation	Reported Accuracy (Typical)	Reference
DRC-Net	Deep Residual Convolutional Network	>95% on LAMOST stellar classes	[24]
Multimodal Network	Fusion of 2D spectrum + photometric image	~2–5% accuracy gain over spectrum-only	[25]
Fourier Image CNN	Classification via 2D Fourier transform of 1D spectrum	92.9% accuracy, captures periodic features	[33]
TDSC-Net	Incorporation of attention mechanisms	84.3% accuracy on average for 5 types of stellar stars	[26]
ViTs	Global patch relationship modeling	99.4% accuracy for 3-class classification	[27]
MLCCS Exoplanet Detection CNN	High-contrast spectral correlation recognition	Order-of-magnitude improvement in detectable planetary contrast ratio	[29]
2D Gaussian Process Framework	Joint wavelength–time correlated noise modeling	Realistic uncertainty estimation up to a factor of ~2	[30]

Note: For [29], task-specific metric; standard accuracy values unavailable. All approximate improvement percentages and multiple-fold performance values are summarized from corresponding cited references; the promotion scope is restricted to the experimental datasets and test settings described in the original literature.

Key Trends:

(1) From Physics to Data: The field shows a clear trajectory from algorithms based solely on physical optics (e.g., the 2D scattered light correction model of Valenti et al. [2]) to hybrid and purely data-driven methods (e.g., MLCCS [29]).

(2) Accuracy Gains: Model-based extraction methods consistently report 20–50% reductions in flux error compared to simple aperture methods [10–12]. Deep learning classifiers routinely exceed 95% accuracy on well-defined tasks [24,25].

It should be clarified that these percentage improvements in flux error are evaluated for spectral extraction accuracy, which are not directly comparable to the order-of-magnitude gain in high-contrast detection sensitivity for exoplanet atmospheric signals mentioned in the following Trend 3, as they correspond to different evaluation dimensions and scientific tasks.

(3) Detection Sensitivity: AI-based detection methods like MLCCS promise order-of-magnitude improvements in contrast sensitivity for exoplanet spectroscopy [29].

(4) Uncertainty Realism: Advanced statistical models like the 2D Gaussian Process framework reveal that simplified noise treatments can misrepresent uncertainties by factors of ~2 [30].

6. Persistent Challenges and Future Directions

Despite remarkable progress, significant hurdles remain on the path to fully automated, reliable, and physically interpretable 2D spectral processing.

Computational Scalability is a primary concern. Techniques like blind deconvolution, training large ViTs, and running 2D Gaussian Processes are resource-intensive. Notably, early physically rigorous 2D correction pipelines, represented by the iterative scattered light removal algorithm of Valenti et al. (2002) [2], inherently involve multi-iteration loops and multi-kernel convolution operations. Such physics-complete frameworks inevitably bring considerable computational complexity and resource occupation, and are difficult to scale efficiently to the high data throughput of contemporary large-area spectroscopic surveys. This inherent limitation of classical model-driven methods further highlights the rationality and necessity of adopting GPU acceleration, parallel scheduling, and optimized lightweight pipelines in future spectral data processing. Processing data from future facilities like the Extremely Large Telescope (ELT) spectrographs is challenging. Meanwhile, the Vera C. Rubin Observatory (LSST) will produce an enormous volume of photometric data and transient alerts, which require extensive rapid spectroscopic follow-up observations. This trend imposes new technical demands on the existing 2D spectral correction and extraction algorithms summarized in this review.

Generalizability and Robustness of data-driven models is another challenge. A CNN trained on LAMOST data may perform poorly on spectra from a different instrument with distinct resolution, dispersion, or systematics. Such cross-instrument performance degradation essentially arises from inconsistent detector response curves, varying spectral dispersion solutions, and unique instrumental systematics between different spectrographs, which constitute the core barrier for model cross-facility transfer in practical 2D spectral reduction. Techniques like domain adaptation, data augmentation using instrument simulators, and the development of 'foundation models' pre-trained on vast, multi-instrument datasets are promising avenues to create more versatile tools.

For homologous data (e.g., different astronomical spectral data), deep learning models generally maintain acceptable overall performance even when key parameters such as spectral resolution differ noticeably. In most cases, only minor adaptive tuning of model parameters is required to achieve satisfactory results.

In contrast, for heterologous data (e.g., applying spectral-processing models to photometric images), the generalization ability becomes extremely poor, and direct migration is hardly feasible.

Interpretability and Physical Consistency are critical for scientific discovery. While a deep network may classify a spectrum accurately, understanding why it did so is often difficult. General explainable artificial intelligence (XAI) tools, such as LIME [34] and SHAP [35], provide model-agnostic feature attribution to interpret black-box predictions locally. Nevertheless, generic XAI cannot fully satisfy physical interpretability requirements in astronomical spectral analysis. For attention-based networks like TDSC-Net, a more reliable domain-specific validation is to examine whether highlighted spatial and spectral regions align with physically meaningful emission/absorption lines and known astrophysical priors. Such cross-checks help constrain spurious attention responses and ensure that network decisions follow physical logic, rather than relying solely on statistical patterns.

Based on the current technical bottlenecks and practical application constraints of 2D spectral image processing, several realistic and constrained future research directions are worthy of in-depth exploration, rather than merely relying on emerging popular technologies. Each prospective direction is analyzed, combined with existing industry limitations and implementation prerequisites as follows:

- End-to-End Differentiable Pipelines. Traditional spectral reduction pipelines adopt segmented processing modes with isolated independent modules, which easily cause cumulative error loss and cannot achieve global optimization. Constructing fully differentiable processing frameworks covering the full workflow from raw 2D detector images to final scientific parameter output can realize joint optimization of each processing link and standardized error propagation. However, this direction still faces realistic constraints, including high computational resource consumption and difficulty in fitting complex instrumental system errors, and its practical deployment requires further compatibility adaptation with mainstream telescope spectral data characteristics.
- Simulation-Based Training. The scarcity of high-quality labeled real 2D spectral data, especially the extreme lack of samples for rare celestial objects, has long restricted the generalization performance of deep learning models in spectral processing. Utilizing high-fidelity instrument simulators to generate massive standardized labeled spectral datasets can effectively compensate for the shortage of observational data. Nevertheless, this method has inherent limitations: simulated data cannot fully replicate complex real-world noise, instrumental artifacts, and atmospheric interference in actual detector imaging, and model performance trained by simulated data often degrades when migrating to real observation scenarios, requiring continuous optimization of simulation authenticity.
- Real-Time Analysis for Time-Domain Astronomy. With the rapid development of time-domain survey telescopes, massive streaming 2D spectral data are generated continuously, putting forward urgent demands for low-latency data processing. Deploying lightweight, efficient neural network models for real-time spectral classification and celestial anomaly detection is an inevitable trend for dynamic astronomical observation data processing. In practice, however, this direction is limited by the balance between model compression efficiency and processing accuracy; overly simplified lightweight models are prone to missing weak spectral features and misjudging low-signal-to-noise ratio target spectra, which limits their large-scale operational application.
- Tighter Integration of Physics and AI. Pure data-driven deep learning spectral processing methods suffer from poor physical interpretability and weak cross-scene generalization ability. Embedding mature astronomical physical principles (e.g., radiative

transfer equations, spectral dispersion laws) into neural network architectures to build physics-constrained hybrid models can combine the flexibility of AI feature extraction and the robustness of physical laws. The core challenge of this mainstream development direction lies in the conflict between fixed physical constraints and flexible data fitting, as well as the difficulty of designing compatible physical-embedded network structures, which remains a key breakthrough point for subsequent 2D spectral intelligent processing research.

7. Conclusions

The processing of 2D spectral images has evolved from a niche calibration task into a rich, interdisciplinary field at the heart of modern observational astrophysics. This review has chronicled this evolution through three interconnected waves of innovation. The first wave established rigorous, physics-based algorithms to tackle fundamental artifacts like scattered light, sky background, and geometric distortion, moving decisively beyond the limitations of 1D extraction. The second wave harnessed the power of ML, first for specific corrections and then, explosively, through deep learning for high-level tasks like classification and ultra-faint signal detection. We are now entering a third wave characterized by the development of accessible software tools, advanced statistical frameworks for uncertainty, and the nascent integration of physical models with AI architectures.

The comparative analysis reveals that no single approach is universally superior; the choice of technique depends critically on the specific instrument, scientific goal, and available computational resources. The enduring strength of physics-based models lies in their interpretability and reliability for well-understood systematic effects. The unparalleled power of deep learning lies in its ability to recognize complex patterns and excel at tasks difficult to codify with rules. The most promising path forward lies not in choosing one paradigm over the other, but in their thoughtful synthesis. As spectroscopic surveys grow larger and more complex, the continued development of scalable, robust, and physically grounded 2D processing algorithms will remain indispensable for transforming raw detector counts into profound discoveries about the universe.

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