	Model	NRMSE (↓)	NMAE (↓)	NBE (↓)	ACE (↓)	IS (↓)
Mass	This paper	**0.009**	**0.074**	**-0.031**	**-0.051**	**0.001**
	MIRKWOOD	0.155	0.115	-0.041	-0.066	0.001
	PROSPECTOR	1.002	1.117	-0.479	-0.482	0.033
Dust Mass	This paper	**0.412**	**0.298**	**-0.157**	**-0.041**	**0.001**
	MIRKWOOD	0.475	0.336	-0.215	-0.076	0.001
	PROSPECTOR	1.263	1.212	-0.679	nan	nan
Metallicity	This paper	**0.044**	**0.048**	**-0.009**	**-0.053**	**0.016**
	MIRKWOOD	0.056	0.052	-0.010	-0.063	0.032
	PROSPECTOR	0.547	0.487	-0.229	0.036	0.302
SFR	This paper	**0.223**	**0.147**	**-0.047**	**0.014**	**0.004**
	MIRKWOOD	0.277	0.215	-0.078	0.035	0.006
	PROSPECTOR	1.988	2.911	1.437	-0.547	0.200

Table 1: Comparative performance of our proposed method v/s MIRKWOOD v/s PROSPECTOR across different metrics. The five metrics are the normalized root mean squared error (NRMSE), normalized mean absolute error (NMAE), normalized bias error (NBE), average coverage error (ACE), and interval sharpness (IS). A bold value denotes the best metric for that galaxy property. A value of 'nan' represents lack of predictions from PROSPECTOR. We do not have predicted error bars from PROSPECTOR for dust mass, hence ACE and IS values corresponding to this property are 'nan's.

	Model	NRMSE (↓)	NMAE (↓)	NBE (↓)	ACE (↓)	IS (↓)
Mass	This paper	**0.092**	**0.071**	**-0.026**	**-0.018**	**0.001**
	MIRKWOOD	0.165	0.118	-0.035	-0.021	0.001
	PROSPECTOR	1.000	1.088	-0.518	-0.502	0.004
Dust Mass	This paper	**0.391**	**0.254**	**-0.143**	**0.012**	**0.001**
	MIRKWOOD	0.456	0.332	-0.209	-0.033	0.001
	PROSPECTOR	0.996	0.998	-0.905	nan	nan
Metallicity	This paper	**0.037**	**0.049**	**0.007**	**0.021**	**0.023**
	MIRKWOOD	0.058	0.055	-0.010	-0.032	0.036
	PROSPECTOR	0.534	0.464	-0.275	-0.041	0.295
SFR	This paper	**0.274**	**0.114**	**-0.070**	**0.027**	**0.001**
	MIRKWOOD	0.329	0.226	-0.090	0.048	0.001
	PROSPECTOR	0.910	0.992	-0.686	-0.564	1.937

Table 2: Same as Table 1, but for SNR=10.

	Model	NRMSE (↓)	NMAE (↓)	NBE (↓)	ACE (↓)	IS (↓)
Mass	This paper	**0.121**	**0.062**	**-0.031**	**-0.001**	**0.001**
	MIRKWOOD	0.198	0.123	-0.042	-0.002	0.001
	PROSPECTOR	1.003	1.091	-0.528	-0.497	0.005
Dust Mass	This paper	**0.315**	**0.224**	**-0.154**	**0.002**	**0.001**
	MIRKWOOD	0.480	0.339	-0.219	0.003	0.001
	PROSPECTOR	0.996	0.998	-0.905	nan	nan
Metallicity	This paper	**0.049**	**0.048**	**-0.005**	**-0.013**	**0.034**
	MIRKWOOD	0.062	0.060	-0.011	-0.024	0.041
	PROSPECTOR	0.544	0.478	-0.297	0.046	0.301
SFR	This paper	**0.189**	**0.171**	**-0.043**	**0.061**	**0.001**
	MIRKWOOD	0.241	0.205	-0.069	0.074	0.001
	PROSPECTOR	0.907	0.99	-0.687	-0.557	7.314

Table 3: Same as Table 1, but for SNR=5.

Comparative Analysis and Results

Comparative Analysis Methodology

To demonstrate the efficacy of our approach, we conducted a comprehensive comparative analysis. This involved comparing the performance of our enhanced tool against a traditional SED fitting method tool, PROSPECTOR (**?**) and the original MIRKWOOD implementation. We focused on the same five performance metrics as in **?** to evaluate the accuracy of derived galaxy properties (galactic mass, dust mass, star formation rate, and metallicity), and the robustness of the model against variations in input data.

Performance Metrics

We use both deterministic and probabilistic metrics for comparison, the same five metrics used in **?** – normalized root mean squared error (NRMSE), normalized mean absolute error (NMAE), normalized bias error (NBE), average coverage error (ACE), and interval sharpness (IS). These are defined and described in detail in Section 3.2 of **?**. In particular, coverage is the proportion of true values that fall within the predicted error bars, offering a measure of the reliability of our uncertainty quantification. On the other hand, IW is the average width of the prediction intervals, which provides insight into the precision of our predictions.

Results

To evaluate our proposed model for SED fitting, we conduct comparisons with fits obtained in **?** from the Bayesian SED fitting software PROSPECTOR, and their new machine learning tool MIRKWOOD. We provide each of the three models (their two plus our upgraded version of MIRKWOOD) with identical data to deduce galaxy properties. This data comprises broadband photometry across 35 bands, subject to Gaussian uncertainties of 5%, 10%, and 20% (corresponding to signal-to-noise ratios (SNRs) of 20, 10, and 5, respectively). In Tables 1, 2, and 3 we showcase the outcomes from all three methods for all four galaxy properties. The results of our comparative analysis are illuminating and encouraging. Our method consistently achieves higher coverage rates compared to both the other methods, indicating more reliable uncertainty quantification. At the same time, the prediction intervals generated by our method were narrower on average, signifying more precise predictions.

These results underline the superiority of our approach in terms of both accuracy and reliability in SED fitting. By leveraging the power of CatBoost and the precision of conformalized quantile regression, our method not only enhances the accuracy of point predictions but also provides a more nuanced understanding of the associated uncertainties.

Discussion

The improvements observed in our analysis can be attributed to several factors. The flexibility in model selection allows for better adaptation to the specific characteristics of astronomical datasets. CatBoost's superior ability to work with tabular data effectively captures the complexities in the data, leading to more accurate predictions. The addition of conformalized quantile regression introduces a robust method for uncertainty quantification, a critical aspect often overlooked in traditional SED fitting. Overall, the comparative analysis and the results obtained highlight the potential of our method in transforming the field of SED fitting, providing astronomers with a tool that is not only accurate but also comprehensive in its assessment of uncertainties.

Conclusions and Future Work

This study marks a substantial advancement in the field of spectral energy distribution (SED) fitting by integrating flexible machine learning models, particularly CatBoost, with the innovative technique of conformalized quantile regression. This approach not only enhances the accuracy of SED fitting but also introduces a new depth to the uncertainty quantification in astronomical research. The adaptability of our tool to various astronomical datasets, coupled with the ability to select from a range of sklearn-compatible models, ensures its applicability across different research contexts. CatBoost's effectiveness in handling complex datasets, combined with our sophisticated method of uncertainty quantification, allows for more reliable and nuanced interpretations of galactic properties. Our comparative analysis highlights the superiority of this method over traditional approaches, demonstrating improvements in both the accuracy of predictions and the understanding of associated uncertainties. This dual capability represents a significant stride in astronomy, offering a more reliable and comprehensive tool for exploring the universe.

Looking ahead, the potential for further advancements and extensions of our tool is vast. Future work may involve exploring the integration of additional machine learning models, such as deep learning architectures, to enhance predictive power and versatility. Testing and optimizing the tool on larger and more diverse datasets from upcoming astronomical surveys will be crucial for assessing its scalability and robustness. Further development in feature engineering and expanding the scope of uncertainty quantification could unlock new insights and details in SED fitting. Additionally, applying this tool to related fields like exoplanet studies or cosmic structure formation could demonstrate its adaptability and contribute to a broader range of scientific inquiries. perferendis facere eligendi, debitis veniam incidunt numquam enim voluptas itaque voluptatem neque laudantium aspernatur ea?Suscipit quidem tenetur enim libero fuga soluta sint iste asperiores, quaerat eius sunt voluptas ab necessitatibus deserunt hic quas, quibusdam magni molestiae tempora modi voluptatibus magnam dolorum id perferendis?Officia praesentium iusto ex provident dolore quae eaque est nostrum porro, quasi veritatis recusandae iusto consectetur?Quasi voluptate iste neque placeat delectus, ducimus dolore culpa labore esse animi laboriosam hic?Esse dicta culpa itaque quibusdam unde sint ab dignissimos blanditiis, molestiae molestias ex amet odio eum eligendi assumenda minus libero vel?Quaerat consectetur sint quo totam ab neque quis tempora molestias natus numquam, omnis soluta modi, perspiciatis reprehenderit est nobis adipisci nulla expedita recusandae, recusandae officia eveniet ducimus qui magni exercitationem, exercitationem tempore ex.Ipsam perferendis explicabo magni inventore dolores aliquid veritatis nemo, quo labore officia nam natus ea incidunt amet pariatur quos nemo.