A Review of Theoretical Advances and Practical Applications of Conformal Prediction in China

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Abstract. Enhancing the learnability and reliability of machine learning algorithms remains a critical research objective. As a learnable framework, Conformal Prediction (CP) leverages historical data to generate statistically valid predictions for new instances at a specified confidence level. For any predictive model, CP produces prediction sets or regions that are guaranteed to contain the true label with at least the pre-specified confidence level under the assumption of exchangeability. This review highlights pioneering contributions from Chinese research communities to both theoretical advancements and practical applications of CP. Based on a systematic review of the existing literature, we analyse CP's core theoretical strengths and objectively discuss its inherent limitations, such as computational inefficiency and the curse of dimensionality. Furthermore, we evaluate CP's current potential across a range of real-world domains, including biomedicine, cybersecurity, industry, and environmental science. Notably, novel applications such as tea analysis and the identification of traditional Chinese medicine using electronic noses demonstrate CP's versatility and significant practical value.

Keywords: Conformal Prediction · Uncertainty Quantification · Prediction Regions · Machine Learning

1 Introduction

With the advancement of machine learning algorithms, remarkable results have been achieved in increasingly complex tasks. However, while pursuing higher accuracy, enhancing the learnability and reliability of algorithms has become a critical challenge that cannot be overlooked. Researchers have long recognized that as machine learning algorithms grow more complex, they increasingly resemble black-box models, making it difficult to provide meaningful explanations for

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their learning and reasoning processes. This not only introduces reliability risks but also complicates the control of model adaptation to new environments and data. Therefore, endowing algorithms with learnability is of paramount importance.

Nowadays, many approaches have been proposed to solve this problem by building reliable prediction models. Bayesian methods [29] and Gaussian process [12] are classical statistical approaches capable of producing prediction sets, but their results heavily depend on the correctness of prior assumptions, which are often unknown in practical applications [34,44]. Other methods, such as bootstrap-based approaches [98] and quantile regression [23], while effective, cannot guarantee coverage under finite-sample conditions. Unlike these methods, Conformal Prediction (CP) [65], as a model-agnostic framework, can provide reliable prediction regions. Requiring only the exchangeability assumption of data, it guarantees finite-sample coverage. CP's validity has been extensively demonstrated both theoretically and empirically [5,52,65], with successful applications across numerous domains.

Since its introduction by Vovk, Gammerman, and Shafer, CP has gained significant attention from researchers. While its theoretical foundations continue to be refined and various extensions explored [42,43,64], researchers have also uncovered CP's potential for diverse applications. This paper synthesizes key research on Conformal Prediction, with particular emphasis on contributions from Chinese scholars to its development and applications. We quantified the number and publication periods of reviewed papers, with specific annotation of contributions from Chinese research communities. The results are presented in Fig. 1. A notable surge in research interest in CP among Chinese scholars has been observed since 2020, accompanied by an exponential increase in research output.

The following section presents a concise yet rigorous theoretical framework of CP and the remaining sections of this chapter are organized along two main dimensions:

1. **Theoretical advances** - highlighting explorations inspired by classical CP methods and improvements addressing traditional CP limitations;
2. **Practical applications** - covering not only common domains like biomedical engineering, cybersecurity, and industrial control, but also unique investigations in areas like tea analysis and traditional Chinese medicine research.

In addition to reviewing existing studies, the chapter analyses CP's strengths and limitations, along with its application prospects across various scenarios. Finally, the conclusion section elucidates CP's significance in enhancing algorithmic learnability.

In summary, this chapter's contributions to the CP research community include:

– A systematic review of contributions from the Chinese research community to CP, encompassing both theoretical advances and practical innovations.

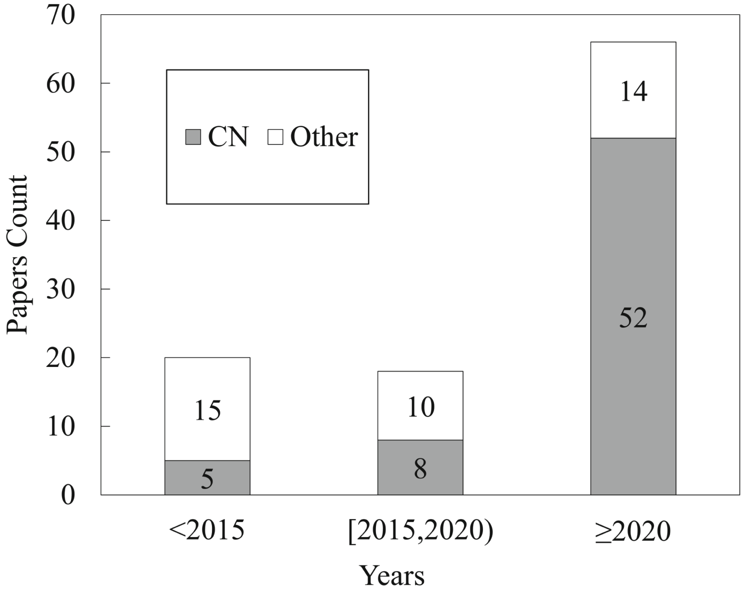


Fig. 1. Number and publication period of the reviewed papers. "CN" indicates contributions from Chinese scholars. Research output from Chinese scholars has shown consistent annual growth, with an exponential increase in recent years

- An introduction to a novel application of the electronic nose-based gas identification system, focusing on tea and traditional Chinese medicine.
- A comprehensive synthesis of applied CP implementations, including theoretical insights and performance comparison, to help propel the advancement of CP deployment.

2 Framework of Conformal Prediction

The framework of classical CP is remarkably concise. For an observed training set of $n-1$ examples Z: $\{(x_1, y_1), ..., (x_{n-1}, y_{n-1})\}$ where $z_i = (x_i, y_i)$ consists of a feature vector x_i and its corresponding label y_i, a machine learning model learns from Z to map a new sample x_n from the sample space X to its label $\hat{y}_n$ in the label space Y. Unlike traditional machine learning algorithms, a conformal predictor can give a prediction set $\Gamma^{\varepsilon} \subseteq Y$ with a user defined confidence level $1-\varepsilon$, where ε is a given additional parameter representing the significance level. The confidence level $1-\varepsilon$ indicates how much confidence the predictor has for that the prediction set Γ^{ε} covers the true label. In other words, CP guarantees that the prediction set will include the true label with a probability at least of the specified confidence level, assuming the data points are exchangeable:

$$P(y_n \in \Gamma^{\varepsilon}) \geq 1 - \varepsilon.$$

This guarantee is known as validity and is a key advantage of conformal prediction. While validity is crucial, it is also desirable to make the prediction sets as small as possible to provide more precise and informative predictions. Efficiency refers to the size of the prediction set. CP makes it possible to avoid worrying about validity and to focus only on improving efficiency.

The foundation for CP's ability to produce prediction sets lies in its use of a nonconformity measure (or score), which quantifies how well a new sample (x_n, y) conforms to previously observed data. By extending the dataset Z to include (x_n, y), the nonconformity measurement α_i for each sample $z_i (i = 1, 2, ..., n) \in Z$ is calculated using a measurable function A:

$$\alpha_i = A(\{z_1, ..., z_{i-1}, z_{i+1}, ..., z_n\}, z_i), \quad i = 1, ..., n,$$

where A is determined by both the specific task type and the underlying algorithm, with the resulting α_i always being a real number. For example, a common nonconformity measure in K nearest neighbours (KNN) is the ratio of distances to the nearest neighbours of the same class versus those of different classes.

The nonconformity measurement enables to assess how well a new sample x_n with a hypothetical label y conforms to observations already seen, from which p-values can be derived for each potential label $y \in Y$ of x_n. For a classification problem with every potential label $y \in Y$ for x_n, the nonconformity measurement is calculated and denoted as α_n^y, then the corresponding p-value p^y is defined as:

$$p^y = \frac{|\{i = 1, ..., n \,|\, \alpha_i^y \geq \alpha_n^y\}|}{n}.$$

The p-value, which lies between $1/n$ and 1, indicates the fraction of the samples in the set containing both observed data and the new sample as nonconforming as $z_n = (x_n, y)$. For a potential label y for x_n, if the corresponding p-value p^y is small, then y is unlikely to be the true label of x_n. If it is large, then we can be highly confident that this label is the true label.

The significance level ε indicates the required confidence level for constructing the prediction set, defined as:

$$\Gamma^{\varepsilon}\left((z_1, z_2, ..., z_{n-1}), x_n\right) = \{y \,|\, p^y > \varepsilon\}.$$

The prediction set construction process can be summarised as follows: for each candidate label y, after incorporating (x_n, y) into the previously observed data Z to form a new set, if the proportion of examples that conform worse or the same as (x_n, y) (measured by the p-value) exceeds the predefined significance level ε, then y is included in the prediction set. In other words, for each label y in the prediction set, we are highly confident that the p-value of (x_n, y) is greater than ε, or the proportion of examples that conform equally poorly or worse than (x_n, y) will exceed ε. Moreover, the confidence level $1 - \varepsilon$ provides a quantitative reference for how confident we can be.

3 Theoretical Advances in Conformal Prediction Research

3.1 Research Inspired by Conformal Prediction's Properties

Conformal Prediction is a statistically rigorous framework that combines the theoretical guarantees of statistical theory with the flexibility of machine learning. Its core strength lies in providing mathematically sound uncertainty quantification while remaining model-agnostic, making it a powerful and reliable foundation for trustworthy AI systems. When integrating with neural network models, CP further enhances predictive reliability [55]. The unique theoretical advantages of CP not only distinguish it from other machine learning algorithms, but have also inspired extensive research aimed at enhancing its performance and broadening its range of applications.

Strict Mathematical Guarantees. CP is grounded in rigorous mathematical principles, providing non-asymptotic and distribution-free statistical guarantees. These guarantees hold regardless of the underlying data distribution or model structure, relying only on the relatively mild assumption of data exchangeability. This property ensures the framework makes no assumptions about the data distribution form, remains agnostic to model architecture, and maintains compatibility with any prediction model. Any algorithm improved upon CP that maintains its rigorous statistical guarantees can thereby establish its mathematical soundness at its core.

Wang et al. [69] conducted a theoretical analysis of the asymptotic properties of a CP variant—locally weighted jackknife prediction (LW-JP). LW-JP incorporates the nonconformity scores into the jackknife prediction [24], which is designed for regression problems with heteroscedastic errors. Unlike traditional conformal prediction, jackknife prediction does not rely on the possible y of the new example x_n; instead, the nonconformity measurements of training examples are computed solely based on the training set Z itself. Specifically, the nonconformity measurement of jackknife prediction is calculated as follows:

$$\alpha_i = A\left(\{z_1, ..., z_{i-1}, z_{i+1}, ..., z_{n-1}\}, z_i\right), \quad i = 1, ..., n-1.$$

Thus, the nonconformity measurements of observed data can be calculated offline and reused for all candidate label y, making LW-JP more computationally efficient than the standard conformal prediction framework. LW-JP employs the absolute loss normalized by the square root of the estimated variance as its nonconformity measure, in contrast to the simple absolute loss used in conventional jackknife prediction.

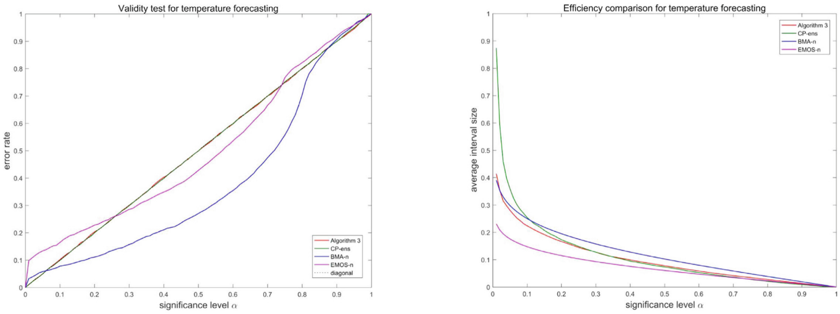
The study provides a rigorous theoretical analysis of LW-JP under asymptotic conditions where the number of training samples approaches infinity. Under appropriate regularity assumptions, the asymptotic validity of LW-JP was proven for nonlinear regression scenarios with heteroscedastic errors. Building on this theoretical foundation, the authors developed two novel conformal regressors based on LW-JP, which achieved state-of-the-art performance, demonstrating empirical validity and improved informational efficiency in experimental evaluations.

An Interval Estimation Under Certain Confidence. Compared to traditional machine learning algorithms, CP-based methods can produce confidence sets or intervals for predictions with guaranteed coverage probabilities. This makes CP naturally suited not only for probabilistic inference problems, but also enables transparent model performance evaluation that surpasses conventional point-estimate metrics like accuracy and mean square error (MSE). When configured to output single predictions, CP can additionally provide credibility and confidence measures, thereby enriching the evaluation metrics for individual point estimates. Credibility is the largest p-value that indicates how reliable the best choice of prediction y in the label space Y is, based on its conformity to the training observations. Confidence is $1 -$ the second largest p-value that indicates how reliable the best prediction y is, based on the exclusion of other possible choices of prediction.

Distribution regression is a specialized regression task where the inputs are probability distributions (theoretical or empirical) rather than conventional feature vectors [9,24,38,57,58]. Typical applications include medical diagnosis [47], where the inputs are derived from multiple measurements of a patient's physiological conditions, and meteorological forecasting [11], where the inputs come from multiple numerical weather prediction models. CP-based predictive models provide statistically valid predictions at specified confidence levels, making them both theoretically sound and empirically suitable for distribution regression tasks.

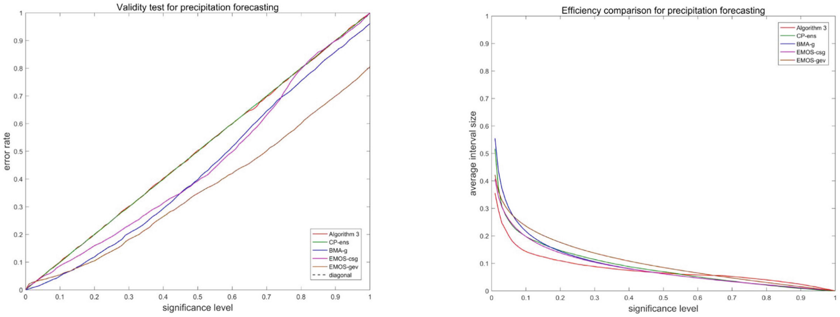
Wang et al. [68] pioneered the extension of CP to distribution prediction tasks and applied it to the post-processing of ensemble predictions. The input distributions are first embedded into a Hilbert space via kernel mean embedding [8,39], then processed by a conformal regressor to obtain the final output. Random Fourier features [49] are employed to approximate the kernel for computational efficiency. The algorithm was tested on synthetic datasets and subsequently applied to statistical post-processing of temperature and precipitation ensemble forecasts. The results of validity test and efficiency comparison shown in Fig. 2 confirm that the proposed algorithm, denoted as Algorithm 3, outperforms other algorithms and serves as a powerful interval predictor for distribution regression problems.

CP's unique capability to quantify uncertainty while guaranteeing prediction set coverage enables applications in optimizing machine learning and neural network architectures [99]. Zhao et al. [100] applied Inductive Conformal Prediction (ICP) to guide neural network pruning, specifically performing filter-level pruning for Convolutional Neural Networks (CNNs). Their approach evolved from initially estimating each filter's contribution to CP prediction efficiency in a coarse manner and removing the least contributive ones, to incorporating computational efficiency through Taylor expansion-based filter contribution



(a) Validity test for temperature forecasting

(b) Efficiency comparison for temperature forecasting



(c) Validity test for precipitation forecasting

(d) Efficiency comparison for precipitation forecasting

Fig. 2. Overall results of the validity test and efficiency comparison [68] for the post-processing of ensemble forecasts for temperature and precipitation. The proposed algorithm is denoted as Algorithm 3. CP-ens refers to a conformal regressor which is built directly on the ensemble forecasts. BMA refers to Bayesian Model Averaging. EMOS refers to Ensemble Model Output Statistics. The suffixes -n, -g, -csg, and -gev correspond to the normal, gamma, censored shifted gamma, and censored generalized extreme value distribution, respectively

estimation [37]. Further improvements were achieved by protecting the most critical filters from pruning to enhance overall pruning performance. Extensive experiments evaluated the trade-offs among prediction efficiency, computational efficiency, and network sparsity on three image datasets (SVHN, CIFAR-10, and CIFAR-100) using two network architectures (VGG16 and ResNet18). The results show that predictive efficiency does not degrade significantly, even when up to 60% of filters are pruned, although more computation time is required compared to the magnitude-based method. Empirical coverage across all experiments is approximately 99.0%, demonstrating the validity property of CP.

Extension to Online Data Augmentation. CP can quantify the nonconformity between newly observed samples and existing data. This property enables its application to online prediction tasks such as data augmentation, where high-reliability unlabeled samples are selectively added to the dataset.

Liu et al. [26] proposed an ensemble ICP-based online learning method (EICP) for data augmentation to address the labour-intensive and time-consuming challenge [90] of annotating training data in electronic nose-based traditional Chinese medicine recognition tasks. Under experimental conditions with varying training set sizes and Gaussian noise introduced to simulate sensor drift, the proposed method was compared against four alternative data augmentation strategies including standard ICP. The results, illustrated in Fig. 3, provided a systematic analysis of different augmentation approaches, demonstrating that the novel EICP method is both effective and robust in enhancing the generalization capability of classification models.

3.2 Dilemmas in the Application of Conformal Prediction

The limitations of CP fundamentally reflect a trade-off between statistical rigor and real-world complexity. While CP relies on rigorous mathematical proofs to ensure theoretical consistency, its computational process can be highly demanding. Moreover, real-world data often contain complex dependencies and noise, which can reduce efficiency and increase risks in traditional CP implementations.

Computational Inefficiency. A key limitation of existing CP-based regression methods is their computational inefficiency, despite CP's theoretical and practical effectiveness. Traditional CP employs a transductive framework, which requires computations involving all previous samples for each new prediction, resulting in substantial computational costs. Inductive CP was specifically developed to address this limitation. Additionally, optimizing the computation of nonconformity measures presents another avenue for improving CP's efficiency.

Disadvantages of the Classic CPKNN. The performance of CP is closely tied to the machine learning algorithm it incorporates. For instance, the widely-used CPKNN [46] method combines KNN's local adaptability with CP's rigorous statistical guarantees, demonstrating strong performance in nonparametric prediction tasks. The CPKNN method leverages KNN's flexibility in distance metric selection (e.g., Euclidean, Mahalanobis, or domain-specific measures like structural similarity in medical imaging) to compute nonconformity measures, while KNN's training-free properties naturally align with CP's transductive framework - particularly advantageous for online prediction scenarios. However, the KNN algorithm performs poorly with high-dimensional data and also suffers from computational inefficiency, as processing new samples requires calculations against all existing instances.

The Curse of Dimensionality. CP relies on measuring nonconformity, which becomes increasingly challenging when handling high-dimensional data such as

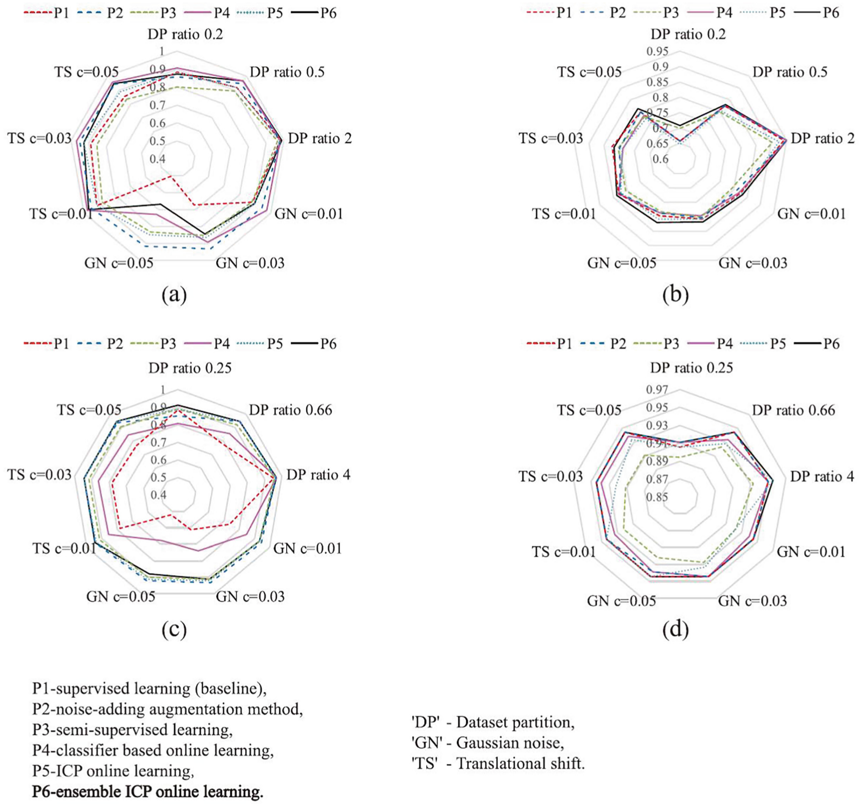


Fig. 3. Experiment results of EICP [26]. Summary of effect on classification accuracy across six processes in nine tasks on two datasets. Median classification accuracy of six processes on dataset 1 with LDA (a), dataset 1 with SVM (b), dataset 2 with LDA (c), dataset 2 with SVM (d)

images or text. In such spaces, traditional nonconformity measures struggle to reliably assess similarity between data vectors. As dimensionality increases, data points become sparse in the high-dimensional space, necessitating larger prediction sets to maintain valid coverage guarantees. This sparsity not only reduces predictive accuracy but also significantly increases memory usage and computational cost, further limiting the efficiency of CP in high-dimensional settings.

Inefficiency in Prediction Sets. CP-generated prediction sets may include excessive low-probability or non-informative candidates to ensure coverage of the true label, which can reduce decision-making efficiency. This reflects CP's inherent conservatism, rooted in the trade-off between statistical rigor and practical utility, and poses challenges for high-precision, high-risk applications such as autonomous driving and medical diagnosis. The redundancy is evident in classification tasks where prediction sets contain multiple low-probability labels, in regression tasks producing excessively wide prediction intervals that far exceed actual fluctuations, and in multi-label tasks where irrelevant labels are included in the output sets.

The Mismatch Between Real Data and Theory. Conformal Prediction theoretically requires exchangeable data, where the ordering of observations does not affect their joint distribution. However, real-world data often violate this assumption, such as strongly autocorrelated time series or spatially/temporally varying distributions. CP's limitations on non-exchangeable data highlight the sensitivity of statistical methods to their foundational assumptions.

3.3 Research on Addressing Conformal Prediction Limitations

Improving Computational Efficiency. Wang et al. [67] proposed a novel conformal regressor based on a CP variant, local-weighted jackknife prediction (LW-JP), which significantly improves computational efficiency. LW-JP computes leave-one-out errors [56] on the training set and correspondingly adjusts its predictions. The study focuses on improving the computational efficiency of CP-integrated algorithms by employing regularized extreme learning machines (RELM) [16] to accelerate LW-JP's computation. RELM enables efficient calculation of the leave-one-out prediction process, which aligns perfectly with LW-JP's requirements, thereby substantially speeding up the entire learning framework. Experiment results show that LW-JP-RELM outperforms ICP-ANN, ICP-SVR, RFNN and RFVN in computational efficiency. In addition, the average results of the validity test are illustrated in Fig. 4. The curve is close to the dashed line, indicating that LW-JP-RELM is a valid predictor in the sense of average performance.

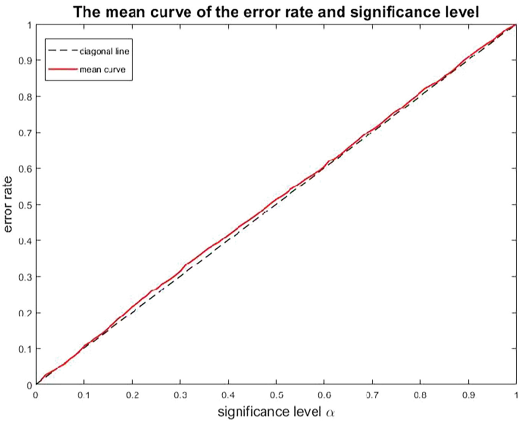
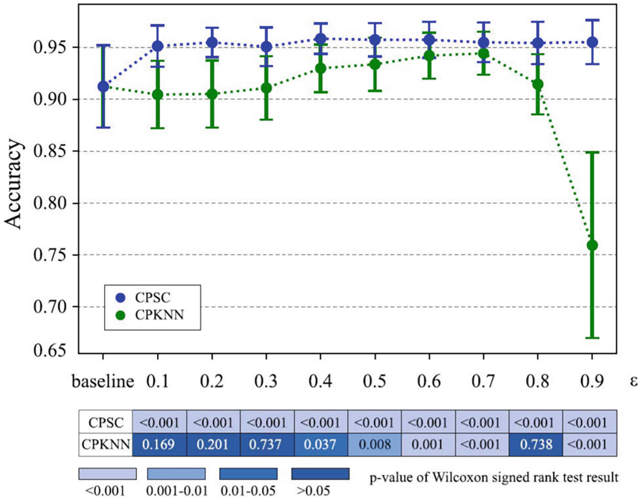


Fig. 4. Average results of the validity test of LW-JP-RELM [67]

Enhancing CP Performance via Integration with Advanced Machine Learning Algorithms. Liu et al. [27] improved the classical CP framework CPKNN by proposing CPSC, which incorporates shrunken centroids [60]. The conventional CPKNN method suffers from high bias and long computation time when processing high-dimensional data [15]. By replacing KNN with shrunken centroids, CPSC effectively regularizes class centroids to eliminate irrelevant features and reduce the sample space dimensionality, thereby yielding more reliable predictions. Both off-line prediction and online prediction with data augmentation are tested on an electronic nose dataset, with the online comparison results shown in Fig. 5.

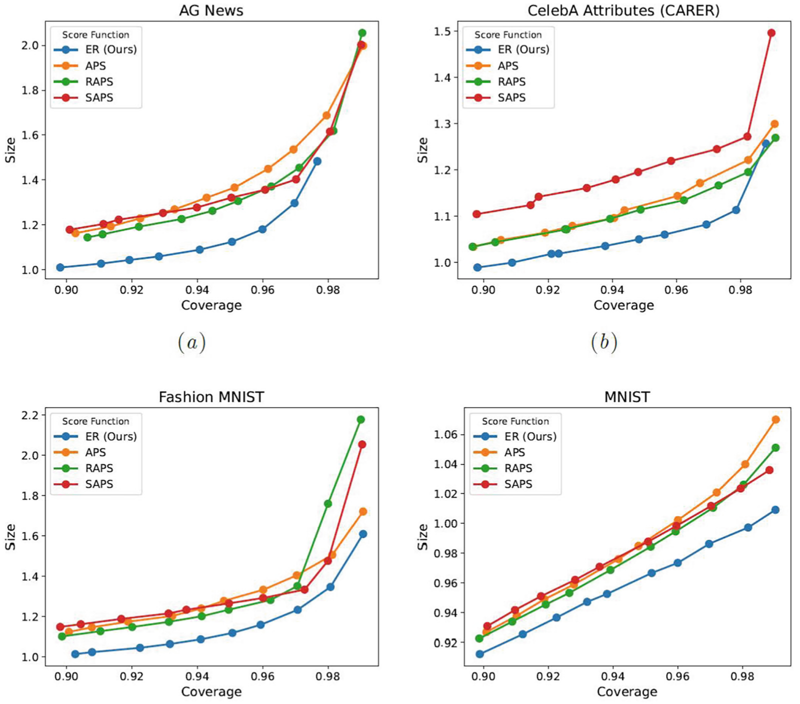


CPSC	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
CPKNN	0.169	0.201	0.737	0.037	0.008	0.001	<0.001	0.738	<0.001

Fig. 5. Online prediction accuracy of CPKNN and CPSC [27] on the testing set with data augmentation under a series of ε settings. Accuracy is calculated using the LDA classifier after completion of the entire data augmentation process

Luo et al. [30] addressed the efficiency degradation of prediction sets caused by using validation sets for confidence calibration in CP classification tasks by proposing an entropy-based reweighted nonconformity measure. This approach simultaneously increases the probability of including the true label in prediction sets while reducing their sizes, thereby improving overall efficiency. Figure 6 shows the coverage-size plots for four datasets: AG News, CelebA Attributes (CARER), Fashion MNIST, and MNIST. The proposed ER score function maintains good coverage while yielding relatively small confidence set sizes.

Enhancing High-Dimensional Data Processing Capabilities. Qian et al. [48] proposed an ensemble CP method based on random projection [1,4] for accurate high-dimensional data classification. The study employs multiple random projection matrices to map high-dimensional data into lower-dimensional spaces and applies CP prediction separately to each low-dimensional representation, which simultaneously serves as a form of data augmentation. A voting strategy [51] is then used to aggregate the predicted classes and refine the prediction sets, achieving a balance between accuracy and prediction set efficiency.



(a) (b)

(c) (d)

Fig. 6. Prediction set size vs. coverage plots for different datasets and score functions [30]. ER refers to the proposed Error Reweighted Conformal Prediction algorithm. APS, RAPS, and SAPS refer to Adaptive Prediction Sets, Regularized Adaptive Prediction Sets, and Sorted Adaptive Prediction Sets, respectively

Improving Prediction Efficiency by Loss Optimization. Wang et al. [66] recognized that traditional CP methods' prediction set construction only controls the coverage loss, making it difficult to constrain redundancy in prediction sets. This implies that regulating the prediction loss could potentially optimize prediction set efficiency to some extent. Moreover, in practical applications such as disease classification using MRI images [6], the specific label categories influence the associated loss, which can be viewed as a class-varying loss. Another example is tumor image segmentation [3], where controlling the false negative rate is of greater concern than merely ensuring prediction set coverage of tumor pixels. Based on this insight, the authors proposed Conformal Loss-Controlling

Prediction (CLCP), extending CP from coverage loss to generic loss control while providing finite-sample guarantees under the exchangeability assumption. By optimizing loss control, the method achieves more efficient prediction sets. The loss-controlling guarantee is empirically verified in classification with a class-varying loss and weather forecasting. Figure 7 shows the results for maximum and minimum temperature forecasting. The preset parameters α and the significance level ε ensure that the prediction loss does not exceed α with confidence $1 - \varepsilon$.

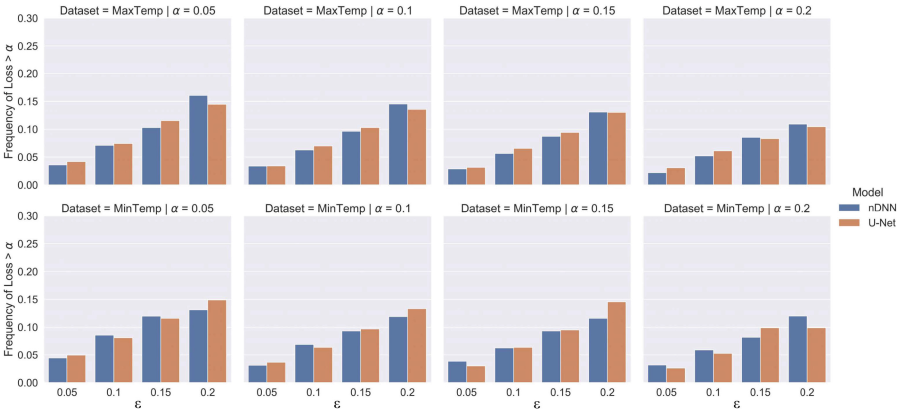


Fig. 7. Bar plots showing the frequencies of prediction losses exceeding the predefined α for $\varepsilon = 0.05, 0.1, 0.15$, and 0.2 on test data for maximum and minimum temperature forecasting. nDNN refers to the naive deep neural network. All bars are at or below the preset ε, empirically confirming the loss-controlling guarantee of CLCP

4 Applications

4.1 Biochemistry and Biomedical

The use of Artificial Intelligence (AI), including machine learning (ML), in biochemistry and biomedical fields has attracted significant attention [63]. In recent years, research in areas such as disease diagnosis, especially cancer detection, and herbal medicine classification has increasingly focused on the reliability and credibility of predictions, rather than settling for approximate results. Conformal Prediction (CP) can achieve reliable predictions by providing the credibility (i.e., uncertainty) for each instance, making it a reliable and compatible machine learning approach for applications in biomedical and biochemical fields [28].

Biomedical. In the biomedical field, CP has shown great potential in areas such as physiological condition detection, cancer detection, and disease diagnosis [33, 61], see Table 1.

Table 1. CP Applications in Biomedical in China

Application	Method	Performance
Blood Pressure Estimation	CP & DER (Deep Evidential Regression) [53]	MAD (Mean Absolute Deviation) of SBP (Systolic Blood Pressure) and DBP (Diastolic Blood Pressure) are 5.56 and 3.18 mmHg, with coverage rates of 94.8% and 95.9%. Uncertainty intervals improve reliability for hypertension diagnosis. Patented method [62].
Cancer Detection	CP & KNN [92]	Accuracies of 87.5% (1NN) and 83.33% (3NN), outperforming traditional KNN. Provides confidence and credibility for individual lung cancer predictions.
Disease Diagnosis	Mondrian CP & GBM (Gradient Boosting Machines) [88]	Predicts sepsis mortality risk; improves the credibility and interpretability of predictions; supports clinical decision-making.
Disease Diagnosis	CP & GBM, NDF (Neural Decision Forest), RF, LR (Logistic Regression) [89]	Applies CP to uncertainty estimation in patient selection for sepsis clinical trials; enables customizable confidence levels for predictions.
COVID-19 Risk Stratification	CP-based tri-light warning system using CP & SC (Soft Confidence), LGBM (Light Gradient Boosting Machine), ANN (Artificial Neural Network) [86]	Helps optimize medical resources and improve triage by stratifying hospitalized COVID-19 patients based on risk.
COVID-19 Recovery Time Prediction	CP & XGBoost (Extreme Gradient Boosting) [72]	Provides tight interval predictions for negative conversion time; MAE (Mean Absolute Error) of 3.54 days. The result is shown in Fig. 8.
Depression Diagnosis	CDP (Conformal Depression Prediction) [25]	Provides reliable, uncertainty-aware facial depression predictions with marginal coverage guarantees at any given miscoverage rate; does not require model retraining or assumptions on data distribution.

In physiological condition detection, Ding's team at the University of Electronic Science and Technology of China applied CP to cuffless blood pressure measurement by combining epistemic uncertainty with CP to generate statistically rigorous uncertainty intervals, thereby improving the reliability and accuracy of blood pressure detection [53]. Subsequently, they designed a CP-based blood pressure measurement system to enhance the reliability of non-invasive arterial blood pressure measurements in clinical settings [62].

In cancer detection, early diagnosis of lung cancer can greatly reduce its mortality. However, diagnostic misinterpretation and erroneous predictions of lung cancer can cause serious psychological and financial burden on patients and their families. Thus, the reliability and credibility of disease diagnosis are crucial. Li's team at Zhejiang University used a gas sensor array to detect the

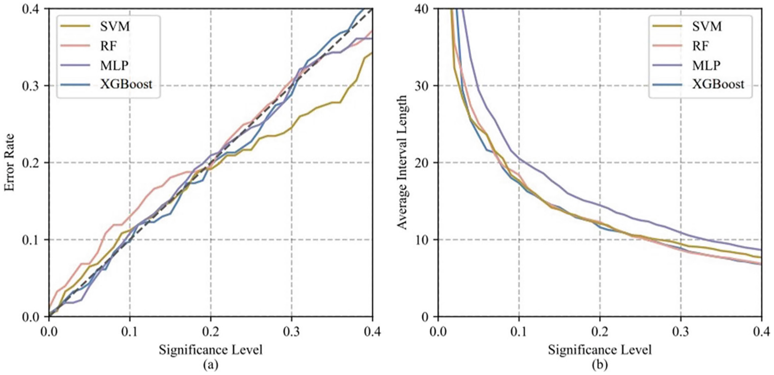


Fig. 8. Distribution of error rates and average interval lengths of the models at different significance levels [72]. (a) Curves showing the relationship between error rate and significance level. (b) Curves showing the relationship between average interval size and significance level (MLP: multilayer perceptron)

exhaled gases of lung cancer patients and healthy individuals and then applied the CP algorithm based on KNN to predict and classify lung cancer [92]. For each case, this method not only provided a diagnostic result but also quantified the confidence and credibility of the diagnosis, significantly improving the reliability of the diagnostic result and aiding doctors in making optimal decisions.

Electronic Nose. The electronic nose, also known as an artificial olfactory system, is a novel bio-inspired detection instrument designed to mimic human olfactory processes. It offers the advantages such as fast and stable performance, low cost, and non-destructive testing. With the rapid development of computational science, it has become a hot research topic to use statistics and machine learning methods to extract relevant information from the signals of electronic noses. Moreover, evaluating the credibility of the predictions is essential when making predictions based on electronic nose data, as it reflects the reliability of the prediction.

The electronic nose can be used in classification of aroma pattern. For tea classification, the primary standards are aroma, color, and taste, with aroma considered the most important. To quantify this phenomenon, Nouretdinov et al. designed a gas sensor-based electronic nose system to distinguish between four different types of tea [41]. To improve the reliability of multi-class tea classification, they proposed a new non-conformity measure for the implementation of conformal predictors based on Support Vector Machine (SVM). Empirical results showed the good performance of the implemented conformal predictor.

Table 2. CP Applications in Electronic Nose in China

Application	Method	Performance
Application	Method	Performance
Electronic Nose	CP-based SVM [41]	CP-SVM with a new non-conformity measure for multi-class classification; overall forced prediction accuracy: 89.7%; error rate controlled by selecting a suitable confidence level.
Electronic Nose	CP-based KNN [77]	CP-KNN for ginseng classification; accuracy: 84.44% (1NN), 80.63% (3NN); the result shown in Fig. 9.
Electronic Nose	CP-based KNN [91]	CP-KNN for classification of 12 herbal medicine categories; accuracy: 91.50% (1NN), 92.17% (3NN).
Electronic Nose	Online CP-based KNN [90]	Online CP enhances model adaptability and improves classification accuracy over time for 12 types of herbal medicines.
Electronic Nose	Aggregated CP-based SVM, RF [75]	Aggregated CP framework for classifying 10 dendrobium species; accuracy close to 80%, with an average improvement of 6.2%.

In China, experienced traditional Chinese medicine practitioners often identify the type of medicinal herbs based on taste and appearance. Taste is the most difficult attribute to quantify, and the classification of Chinese medicinal herbs often requires extensive experience. Because different herbs have different medicinal properties, incorrect usage can worsen the condition and cause significant adverse effects. To address this, Li's team at Zhejiang University conducted a series of studies on reliable classification of Chinese herbal medicines using electronic noses. In study [36], they discussed the classification of ginseng samples using CP and Venn prediction, both of which provided reliability estimates for the predictions. Similarly, for ginseng sample classification, they proposed a CP predictor based on KNN in [77], which not only outperformed traditional KNN but also provided reliability estimates for each prediction. Subsequently, they expanded the classification and recognition of herbal medicines. In [91] and [90], they proposed both online CP and CP-based KNN classification methods to classify 12 types of visually similar herbal medicines using the electronic nose. Both methods achieved reliable and accurate classification predictions. In a further study on valuable herbs such as Dendrobium, they developed a method to distinguish between 10 different species using the electronic nose [75]. The method applied aggregated conformal prediction and achieved nearly 80% classification accuracy while providing reliability assessments for each prediction. The CP applications on electronic nose in China are summarised in Table 2.

Bioelectronics. Neurophysiological signals, such as electroencephalogram (EEG) and electromyography (EMG), are important indicators of human physiological states and can provide insight into human cognition and perception.

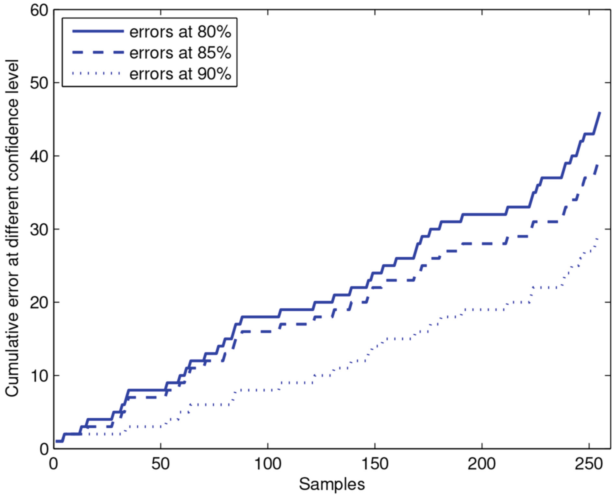


Fig. 9. Experimental results of discrimination of Ginseng [77]

These signals have significant implications for clinical diagnosis and neuroengineering. CP provides theoretical support for quantifying uncertainty in signal analysis, showing significant value in EEG and EMG applications [2] (Table 3).

Table 3. CP Applications in Bioelectronics in China

Application	Method	Performance
EEG	KIII model [93]	TCM (Transductive Confidence Machine) applied with the KIII model for recognition of brain hypoxia EEG signals; controls and assesses of risk associated with each prediction.
EMG	ICP & Bi-LSTM & RF [76,94]	Improves the reliability of decoding speech information from EMG; provides confidence regions for individual predictions with a guaranteed error rate; achieves higher accuracy (0.87) than baseline methods.
EMG	CPSC & DRCA [70]	Improves the reliability of taste sensation decoding; CPSC with DRCA significantly improves classification accuracy ($p < 0.05$) across six subjects; enhances reliability in high-dimensional sensor data while reducing computation time.

In EEG signal analysis, to improve the credibility of predictions related to brain hypoxia, Zhang et al. combined the Transductive Confidence Machine algorithm with the KIII model. They proposed a more reliable method for recognizing hypoxia EEG signals with a preset confidence level [93]. This method improved reliable prediction with confidence measures in classifying normal versus hypoxia EEGs, while also allowing for the control and assessment of risk associated with each prediction.

In the EMG domain, because muscle movement is closely linked to neural signals, it is possible to decode human behavior from neuromuscular activity. However, the decoding process is uncertain, making it essential to quantify the confidence of predictions. For example, to decode silent speech from EMG, Wang and Zhang et al. combined Inductive Conformal Prediction (ICP) with machine learning methods such as Random Forest (RF) and Bidirectional Long Short-Term Memory (Bi-LSTM) [76,94]. Their approach not only improved the performance of decoding speech information from EMG but also provided confidence regions for individual predictions with a guaranteed error rate, thereby significantly improving the reliability of the decoding process.

Furthermore, EMG signals can also be used to decode human sensations. Interpreting these sensations is particularly challenging due to the high levels of noise in EMG signals and the significant individual differences in signal strength. These factors greatly affect the reliability and accuracy of predictions, as well as the generalizability and transferability of the model. For example, human taste sensation can be qualitatively described using surface electromyography (sEMG), and improving both reliability and cross-user classification performance is crucial for effective recognition. To address this, Wang et al. proposed a method that combines Domain Regularized Component Analysis (DRCA) and Conformal Prediction with Shrunken Centroids (CPSC) [70]. Their approach aims to improve the cross-user classification performance through the following steps:

1. Build a model using training data from the source domain;
2. Predict the labels of active data from the target domain;
3. Quantify the reliability of the predictions in terms of credibility and confidence;
4. Filter predictions with high credibility;
5. Augment the training data with the selected high-confidence samples.

Ultimately, their method achieved high classification accuracy in distinguishing among the six basic taste sensations. It also effectively addressed the issue of cross-user data distribution drift and improved prediction reliability.

4.2 Cyber Security

CP has made significant progress in recent years in the field of cyber security, offering new perspectives and methods to address the complex and ever-changing nature of network threats. Recent studies have explored its applications in areas such as 6G communication systems [14,40], Android malware detection [10,45], and botnet identification [7,22]. CP has also demonstrated unique advantages in tasks such as server decision-making, intrusion detection, and anomaly behavior monitoring [5]. Table 4 summarises its applications in China.

Table 4. CP Applications in Cyber security in China

Application	Method	Performance
Wireless Federated Learning	WFCP [103]	Achieves small and informative prediction sets under noisy wireless channels, enhances reliability and communication efficiency.
Intrusion Detection	Enhanced SVM [17,21]; Multi-model CP [79]	Improves detection accuracy and provides confidence and reliability estimates; patented method [20]; Multi-model fusion for malicious code enhances robustness and prediction reliability.
Unknown Threat Intelligence	LSTM /XGBoost [97]	Maintains error rate below 2.5% and achieves F1 score $>$ 90% for DGA (Domain Generation Algorithm) domain detection, supports secure and reliable threat propagation; patented method [78].
Log Anomaly Detection	Statistical learning method with CP [13,50]; Multi-confidence-guided anomaly detection (Multi-CAD) [84]	Achieves dynamic adaptation to changing logs and improves F1 score by 1.6–1.9% points; Multi-CAD model reaches 98.2% accuracy using feedback from CP-based non-conformity scores.
Network Traffic Prediction	MetaSTNet [31]	Provides calibrated prediction intervals with high accuracy, ensures reliable performance on real-world traffic datasets; patented method [87].

One notable study, Wireless Federated Conformal Prediction (WFCP), proposed by Zhu et al. [103], aims to enhance the reliability and efficiency of joint data processing between devices and servers over wireless channels using Conformal Prediction. In this framework, devices communicate statistical information about their local data to the server, enabling it to make more reliable predictions and ensure that each prediction falls within a predefined confidence range, even under noisy communication conditions.

Acquiring and utilizing unknown network threat intelligence remains one of the key challenges in the field of cyber security. Wang et al. [97] proposed a network threat intelligence propagation method based on CP, incorporating confidence and reliability assessment parameters into the LSTM and XGBoost algorithms. This integration allows the model to quantify prediction reliability, while controlling the error probability in propagation of unknown intelligence.

More recently, a deep learning-based model called MetaSTNet transfers the meta-knowledge to real-world environments to achieve accurate predictions [31]. The model is further deployed with Cross Conformal Prediction (CCP) to evaluate the calibrated prediction intervals, providing reliability guarantees for the prediction results as illustrated in Fig. 10. These findings highlight the advantages of CP methods in addressing network traffic prediction problems.

4.3 Industries and Environment

In industrial and environmental domains, the application of CP has been gradually gaining popularity. Table 5 summarises some of its applications in China.

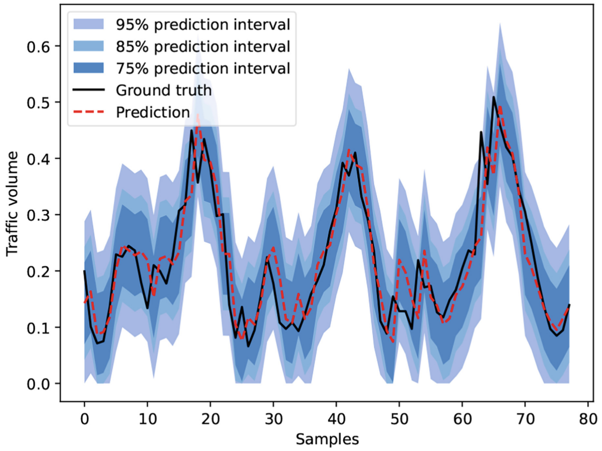


Fig. 10. The experimental results of interval prediction on the MetaSTNet [31]

Table 5. CP Applications in Industries and Environment in China

Application	Method	Performance
Mining (Iron-making)	RVFLN (Random Vector Functional Link Network) [101]; multi-output CP [96]	Faster and more accurate molten iron quality prediction in the blast furnace iron-making process; Improved efficiency of the prediction region under the guarantee of coverage.
Coal Classification	SVM [74]	Classification accuracy $>$ 98.45%, error rate can be adjusted by confidence levels.
Industrial Time Series	Uncertainty quantification framework with CP [95]	Reduced prediction interval width (6.29%, 15.70%) while maintaining 95% coverage.
Distribution Network Topology	CNN [104]	High accuracy, especially when output size is small, with high coverage.
Wind Speed Prediction	CP-Based Support Vector Regression [18]	Improved accuracy and reliability compared to direct prediction methods; supports early warnings to reduce potential downtime and maintenance costs.
Weather Forecasting using Radar Echo	Unet [19]	Enhanced accuracy and reliability of storm forecasts; shows advantages in both point prediction and interval prediction for radar echo extrapolation.
Storm Prediction	CP-based framework [35,71]	Comparable accuracy with operational benchmarks; better reliability via strict uncertainty intervals. Achieved RMSE (Root Mean Square Error) of 7.86 knots, outperforming other comparison algorithms.

CP can be used to optimize production processes by predicting variations in production parameters, thereby improving efficiency and product quality. Wang et al. [74] applied CP to near-infrared analysis for rapid coal classification. By combining CP with SVM through the CV-SVM method, the study achieved fast and accurate coal type identification. Furthermore, by adjusting the confidence level, the model produced results with varying error rates, playing a key role in quality control.

Zhou et al. [95] proposed a novel; uncertainty quantification framework based on CP for industrial time series analysis. The framework integrates global and local nonconformity measure information within the CP structure to dynamically adjust the confidence levels of one-sided prediction intervals. Experiments on wastewater treatment and sintering production datasets show that this method significantly reduced the width of prediction intervals while maintaining the same coverage rate. Building on this work, the team [102] proposed a patent for nonferrous metal smelting, particularly targeting the prediction of alkali liquor concentration.

CP is also gaining traction in the earth sciences [54], particularly in early warning systems for wildfires [85] and floods [32]. For tropical cyclone path prediction, Meng et al. [35] developed a CP-based system using hurricane data from 1975âĂŞ2021 for path forecasting. While maintaining competitive accuracy, the system demonstrated superior reliability in its uncertainty estimates. Similarly Wang's team [71] utilised satellite infrared imagery and CP for cyclone intensity estimation, achieving a lower RMSE of 7.86 knots, outperforming other algorithms. These results illustrate CP's strong potential in forecasting both cyclone paths and intensity.

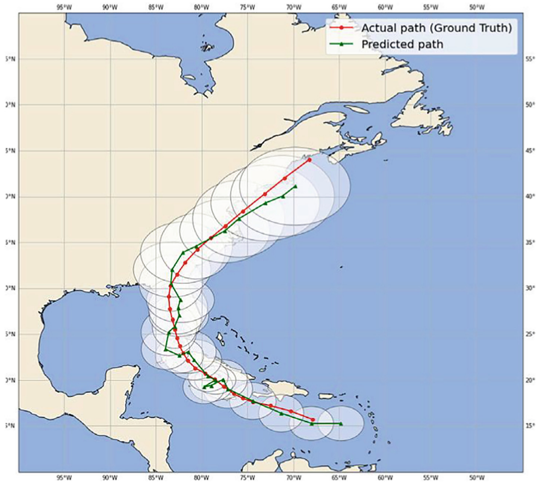


Fig. 11. The hurricane forecast results [71]: red line indicates the ground truth and green line represents the prediction path

4.4 Other Applications and the Lessons

CP has also shown significant potential across a wide range of fields, offering strong support for uncertainty quantification and decision-making in diverse applications, see Table 6.

Table 6. Other CP Applications in China

Application	Method	Performance
Transportation Planning	CQR-GAE (Conformal Quantile Regression Graph Autoencoder) [59]	Improves predictive confidence with strict coverage guarantees; outperforms baseline methods in real-world traffic flow scenarios; enhances robustness of route planning.
Behaviour Recognition	CP-based framework [80–82]	Enables effective set-based predictions for group behaviour forecasting; detects distribution shifts online even in complex environments and with limited sample conditions.
Aerospace	CP-based distribution-free uncertainty quantification method [83]	Provides finite-sample guarantees for trajectory classification and improves trajectory classification accuracy; delivers reliable prediction sets with specified confidence levels.
Finance	OSL-SCN (Online Self-learning Stochastic Configuration Network) [73]	Enhances forecast accuracy and reliability in Bitcoin price prediction; produces confidence intervals for robust financial modeling.

The cross-domain applications of Conformal Prediction (CP) demonstrate its growing importance as a reliable and robust framework for uncertainty quantification. First, CP provides strict mathematical guarantees: it ensures validity under minimal assumptions, promises high accuracy, and maintains that the error rate of predictions does not exceed a user-defined significance level. This is particularly critical in applications such as medical diagnosis, finance, and weather forecasting, where trust in the model is essential. Second, CP's ability to generate interval estimates with adjustable confidence levels enhances reliability over point predictions. It is widely applied in areas such as wind speed prediction, intrusion detection, and industrial process control. Third, CP can adapt to online, streaming, or dynamically changing data, improving system robustness. By measuring the nonconformity of new data relative to historical observations, CP allows real-time uncertainty estimation. This capability is especially valuable in behavior recognition, anomaly detection, and data augmentation for high-dimensional sensor environments. Together, these advantages highlight CP's strong theoretical foundation and practical effectiveness across diverse application domains.

5 Conclusion

This chapter briefly reviewed theoretical advances and practical applications of conformal prediction in China, highlighting key contributions from Chinese research communities.

With the rapid advancement of machine learning algorithms and computing systems, an increasing number of models have been developed to tackle complex tasks. However, the pursuit of higher accuracy has become increasingly challenging due to the growing complexity and over-parameterization of models, which often result in overfitting, reduced interpretability, and weakened generalization performance. Striking a balance between the learnability and reliability has emerged as a critical concern. Although newly developed computing systems have improved the computational process for the learning and reasoning processing of a complex system, they often fail to provide meaningful explanations for model behaviour. This lack of interpretability introduces potential reliability risks and complicates model adaptation to new environments and data.

Conformal Prediction (CP) [65], pioneered by Vovk, Gammerman and Shafer, offers a learnable framework that enhances the reliability of machine learning models. By producing valid and calibrated confidence measures, CP enables models to quantify and communicate uncertainty effectively—an essential feature for robust and trustworthy learning systems. To address computational challenges, several efficient CP variants have been developed, including adaptive CP, local-weighted jackknife prediction (LW-JP) and Loss-Controlling Prediction (CLCP). These innovations have made CP increasingly practical for large-scale and real-time applications.

The availability of well-calibrated confidence information helps learning algorithms adapt to better handle distributional shifts, manage ambiguous inputs, and make more informed updates. This ultimately improves both predictive performance and training efficiency. For this reason, CP has been successfully applied across a wide range of fields, including biomedicine, cybersecurity, industrial control, environmental science and artificial sensation - such as in tea and traditional Chinese medicine classification. Notably, many of these applications are driven by contributions from Chinese researchers. Collectively, these successes show that the CP's significance arises from both the reliability and learnability of the model predictions.

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