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Uncertainty-Aware Hybrid Ensemble Framework for Haze Degree Estimation in Vision-Based Processing Systems

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Abstract

Haze severely degrades outdoor image visibility and color fidelity, limiting the reliability of vision-based systems used in autonomous navigation, environmental monitoring, and aerial surveillance. Existing haze degree estimation approaches either rely on handcrafted priors with limited generalization or deep learning models that behave as black boxes without awareness of uncertainty. To address this gap, we present a Hybrid Haze Degree Estimation (HHDE) framework that integrates interpretable physical haze descriptors with high-level convolutional representations within a probabilistic ensemble learning paradigm. Nineteen haze-relevant features are fused with CNN embeddings and processed using a stacking architecture consisting of Random Forest and XGBoost regressors. At the same time, a Bayesian Ridge meta-learner produces uncertainty-aware haze predictions. HHDE quantifies both haze degree and its corresponding confidence interval, improving reliability in uncertain atmospheric conditions. Extensive evaluation on ten benchmark datasets demonstrates the superior performance of HHDE over classical regression algorithms and state-of-the-art deep learning models, achieving an MAE of 0.0206, an RMSE of 0.0301, and an $\boldsymbol{R^2}$ of 0.9525. Ablation analyses confirm the complementary roles of hybrid feature fusion and Bayesian reasoning. The results establish HHDE as a robust, interpretable, and uncertainty-aware solution suitable for real-world environmental image analysis and autonomous vision systems.

Keywords: Haze Detection, Hybrid Features, Ensemble Learning, Convolutional Neural Network (CNN),Bayesian Ridge Regression,Uncertainty Estimation, Haze Degree Estimation,Image Quality Enhancement

1 Introduction

Haze is a common weather event occurring when dusts, aerosols, and water droplets are scattered in the atmosphere. This scattering considerably decreases the visibility and contrast of an image making it harder to visualize and interpret outdoor scenes. The haze negatively impacts on many applications of the eyes, such as aerial surveillance, motor aids, remote sensing, and environmental scanning. To ensure that such systems can work in practice, the level of haze in captured images should be properly estimated first to allow correct visibility restoration, image amplification, or understanding the scene.

The last ten years have been marked by a lot of research on the estimation of haze and its removal. Older methods are mainly based on physical modeling, and they use the principles of atmospheric scattering and manual priors to derive the properties of haze. Dark Channel Prior (DCP) represents a representative technique which has reported significant success in limited imaging scenarios [1]. Color Attenuation Prior (CAP) represents a technique that represents a contrast-based measure [2]. Their performance however tends to decline in cases of different light environments, where the haze of the scene is not homogenous, and when there is the occurrence of complex geometries of the object. This is based on the fact that they are dependent on deterministic assumptions that do not reflect the variability of actual atmospheres.

To overcome these drawbacks, data-based methods, especially deep learning methods, have become strong alternatives. Convolutional neural networks (CNNs) like DehazeNet [3] and AOD-Net [4] learn haze-related features automatically and directly on large scale datasets which significantly enhances the accuracy of estimation and generalization. Even more recent transformer-based and attention -guided models, such as HazeFormer [5] and TransWeather [6] exhibit very strong quantitative results. Nevertheless, these deep learning models are usually used as black boxes, which are less interpretable and do not provide quantification of uncertainty, which are essential in safety-critical tasks such as UAV navigation and environmental diagnostics.

This interpretability versus adaptability trade-off shows the necessity to have a hybrid learning paradigm that would have the strengths of both physically inspired features and deep representations. Moreover, the majority of currently existing hybrid and ensemble-based haze estimation models are deterministic merely offering isolated point estimates without assessing the confidence in the model or the predictive stability. In dynamic environmental conditions, this uncertainty awareness is very critical in reliable decision-making.

In order to address these limitations, this paper introduces a Hybrid Haze Degree Estimation (HHDE) system, which combines physically interpretable attributes with deep CNN-derived embeddings with a stacking-based ensemble approach. The framework uses Random Forest (RF) and XGBoost (XGB) as the base regressors, and a Bayesian Ridge Regressor (Bayesian Ridge) as the meta-learner, combining predictions and evaluating predictive uncertainty by using a probabilistic formulation. The model can reproduce low-level physical aspects and high-level semantic patterns of haze with this design, in addition to measuring the confidence of each prediction. The key contributions of the research may be summed up as follows:

- A hybrid feature fusion strategy that jointly exploits 19 physical haze descriptors and CNN-derived semantic embeddings, enabling complementary low- and high-level haze perception.
- A probabilistic stacking ensemble that integrates Random Forest and XGBoost regressors with a Bayesian Ridge meta-learner to obtain uncertainty-aware haze degree estimation.
- A confidence-interval mechanism that quantifies prediction reliability, enabling informed decision-making in safety-critical vision tasks.
- A comprehensive evaluation across ten heterogeneous haze datasets, demonstrating consistent generalization to synthetic, semi-real, and real-world scenarios.
- An ablation study confirming the independent and combined contributions of physical features, deep representations, and Bayesian uncertainty modeling.

In contrast to traditional haze estimation methods, which only consider the accuracy of point prediction, the proposed HHDE framework directly captures predictive uncertainty related to haze density estimation. The term' uncertainty' is used in this work to refer to the confidence in the degree of regress haze based on heterogeneous feature representations, informed by physical priors and deep convolutional embeddings. Instead of modeling uncertainty in network weights using either Bayesian neural networks or Monte Carlo dropout, HHDE provides uncertainty at the ensemble regression level, allowing for the use of Bayesian Ridge Regression via stacking. This design will allow propagating feature-level variability and regressor disagreement to the output-level predictive variance. As a result, the proposed solution not only provides the correct estimates of haze degree but also a statistically based confidence interval, which is a more reliable and interpretable answer for vision-based systems when atmospheric conditions change dynamically.

The rest of this paper has been structured in the following way: Section 2 is a review of related work. Section 3 presents the suggested HHDE framework and its elements. Section 4 speaks about the experimental set up, ablation findings, and uncertainty calibration findings. Section 5 will provide the detailed analysis of results and comparison with existing approaches, and then the conclusions will be presented in Section 6 and directions to future working.

2 Related Work

The estimation and removal of haze are a broadly researched computer vision field, image enhancement, and remote sensing. They include six research streams in the existing literature, namely: (i) physical-model approaches, (ii) machine learning-based regression methods, (iii) deep learning models, (iv) transformer-based and generative architectures, (v) ensemble and hybrid methods, and (vi) uncertainty-aware approaches. This section covers each category and draws out their most important developments, constraints and their arrangements to the suggested HHDE framework.

2.1 Physical-Model Approaches

The initial studies on early haze estimation mostly depended on atmospheric scattering models, in particular, the Koschmieder law, to explain the light attenuation by suspended particles. The Dark Channel Prior (DCP) of He et al. [1] was among them, and its claim was that in most haze-free outdoor scenes there are at least two color channels whose pixels have an almost zero intensity. Other extensions like e.g. Color Attenuation Prior (CAP) [2], Haze Line Model [7], and Color-Line Clustering [8] used relations between hues and contrasts to infer scene transmission and light in the atmosphere. Even though these physics-based methods are computationally efficient and interpretable, they usually fail in non-homogeneous or bright sky areas, where prior assumptions fail. They are also deterministic and thus adaptability to different lighting conditions and complex geometries of scenes is curtailed.

2.2 Machine Learning-Based Approaches

To address the inflexibility of handcrafted priors, scholars proposed classical machine learning algorithms in haze degree prediction. Statistical or handcrafted features representing color, texture, and edge cues have been applied with the use of Support Vector Regression (SVR), Random Forest (RF), Gradient Boosted Decision Trees (GBDT) and LightGBM [6]. Although these models are able to deal with nonlinear interactions between features, and their generalization is moderate, they are very sensitive to the quality of manually engineered features. In addition, they do not generally give uncertainty measures, and thus their reliability in decision-critical processes is low.

2.3 Deep Learning Approaches

The development of deep learning has greatly promoted the haze estimation process since it allows the learning of features automatically using raw images. The nuanced method of haze estimation was firstly presented by DehazeNet [3] followed by learning transmission and atmospheric parameters simultaneously. This process was further improved in AOD-Net [4] where an end-to-end architecture is utilized to combine both estimation and reconstruction processes. Later frameworks, such as dense network and multi-scale CNN systems [9] improved generalizaion by learning multi-level haze representation.

In the recent past, attention-based models have been created to capture both global dependencies and local texture variations in the presence of haze, including TransWeather [6] and PDRNet [10] . Although these deep models can be very accurate quantitatively, they are frequently black boxes, i.e. they are uninterpretable, and the prediction confidence is unknown. In addition, their training is intensive in large labeled datasets and high computational resources, meaning they cannot be used in practice.

2.4 Transformer and Generative Approaches

Transformers models have become a new dominant paradigm of vision tasks because of their capability of capturing long-range contextual dependencies. Other models,

including Dehamer [11], Restormer [12], and HazeFormer [13], are convolutional-based backbones with attention layers added to them to dehaze images in the state-of-the-art. Likewise, haze translators based on cycleGAN, such as CycleGAN, haze-free image translators [14], are trained adversarially. Although the results of these approaches are visually impressive, they are also not very interpretable. Also, transformer and GAN-based models are computationally complex, memory-heavy, and deterministic by nature, able to show no uncertainty or confidence in predictions.

2.5 Ensemble and Hybrid Approaches

To combine interpretability and data-driven adaptability, hybrid and ensemble approaches have gained prominence. For example, Chen et al. [15] integrated handcrafted physical features (contrast, intensity, and dark channel) with CNN embeddings for haze estimation. Huang et al. (2023) [16] proposed a hybrid deep regression model combining color attenuation priors with learned deep features, achieving improved robustness. Ensemble methods employing XGBoost and Random Forests have been explored to mitigate overfitting and capture nonlinear relationships among hybrid features [17][18].

However, most hybrid models still operate deterministically, providing single haze degree estimates without modeling uncertainty. This limitation restricts their applicability in high-stakes domains like environmental monitoring and UAV navigation, where model confidence is as critical as prediction accuracy.

2.6 Uncertainty-Aware and Bayesian Learning in Vision

Recently, uncertainty quantification has attracted attention in computer vision and environmental prediction. Bayesian Neural Networks [19] and Monte Carlo Dropout [20] have been applied to model epistemic and aleatoric uncertainties in neural networks. Bayesian Ridge Regression and Gaussian Process Regressors have also been used in environmental modeling to estimate predictive mean and variance [21].

However, probabilistic methods of learning are not investigated deeply when it comes to the haze estimation. This is because the uncertainty-sensitive haze models have not been developed, and the available methods do not distinguish between confident and uncertain forecasts, restricting their reliability in an autonomous or remote sensing system.

To overcome such gaps, Hybrid Haze Degree Estimation (HHDE) framework combines features fusion with Bayesian reasoning stacking in an ensemble framework. HHDE provides both interpretability and uncertainty awareness with the ability to predict the degree of haze accurately and provide a confidence interval by combining both Random Forest and XGBoost as the base regressors and a Bayesian Ridge meta-learner.

The probabilistic formulation allows the HHDE model to measure its reliability and provide a reliable, explainable and high performance solution to the estimation of haze under a wide range of atmospheric conditions. As the literature review indicates, the absence of uncertainty quantification and interpretability is one of the key bottlenecks in deep learning and hybrid ensembles as it has made a significant improvement

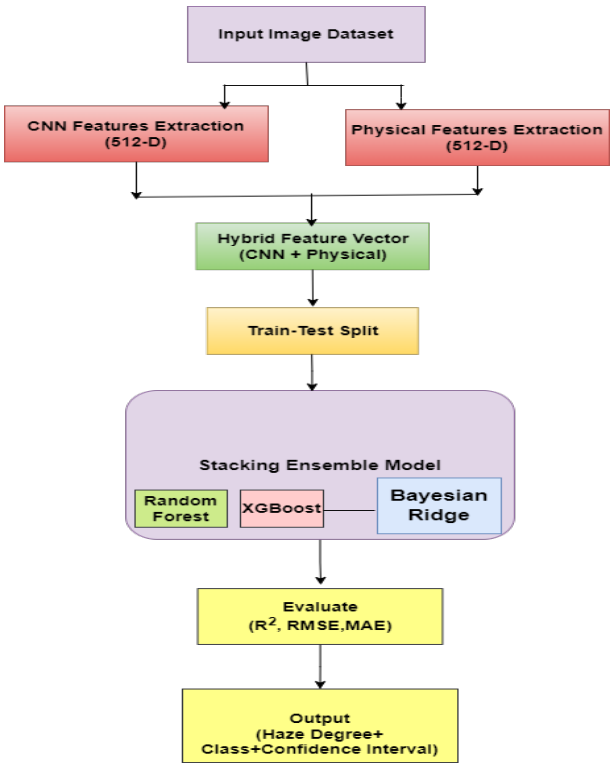


Fig. 1 Flow Chart of State Of Art(SOA)

in the accuracy of haze estimation. The HHDE architecture proposed overcomes these limitations by using hybrid feature fusion and Bayesian ensemble learning, which obtains credible and uncertainty-estimating haze degree prediction at varied environmental settings.

3 Methodology

This section outlines the proposed Hybrid Haze Degree Estimation (HHDE) architecture, to combine physically extracted features and deep convolutional representations into a stacking-based ensemble learning framework as shown in Figure 1.

3.1 Overview of the HHDE Framework

In this section, the review of the HHDE Framework will be given. The hypothesized HHDE model combines two complementary viewpoints on the analysis of haze:

- Physical handcrafted descriptors representing luminance, color and contrast attenuation;
- Deep learning is a constrict that is automated by a lightweight convolutional neural network (CNN).

These are stacked together forming a stacking ensemble architecture where Random Forest (RF) and XGBoost (XGB) are used as a base regressor and Bayesian Ridge Regressor (BRR) are used as a meta-learner. The base learners learn the nonlinear relationships between features whereas the BRR combines the results and learns predictive uncertainty. This is possible through probabilistic integration which allows the framework to make not only an accurate estimate of haze degree but also a confidence interval to every prediction which is essential to reliability under variable atmospheric conditions.

3.2 Employed Dataset

An overview of all the ten datasets employed in this study is provided by Table 1, where NA represents not available.

Table 1 Summary of the datasets employed in this study

S.No	Dataset	No. of HI	No. of HFI	Ground Truth
1	O-Haze [22]	45	45	Yes
2	I-Haze [23]	30	30	Yes
3	D-Hazy [24]	1472	1472	Yes
4	FRIDA2 [25]	264	66	Yes
5	Dense Haze [26]	55	55	Yes
6	IVC	25	NA	No
7	Fine Dust	30	NA	No
8	500IMG	NA	500	No
9	NH-Haze [27]	55	55	Yes
10	RESIDE(ITS) [28]	13990	1399	Yes

HI indicates Hazy Images and HFI indicate Haze Free Images.

IVC, Fine Dust, and 500IMG are non-official datasets that are maintained within an organization and have no formal benchmark publications.

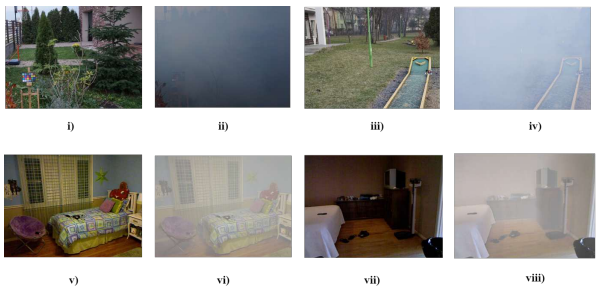


Fig. 2 Illustration of used dataset.

3.3 Haze-Relevant Features

A number of haze-relevant characteristics have been published which shows that low -level visual cues such as saturation, intensity,hue and contrast, have a potential relationship with the amount of haze.As a result, these haze-relevant visual cues can be used as features. The following section gives a brief explanation of the characteristics that are important for haze prediction from a single image.The summary of the most important haze-related visual cues is presented in Table 2.

Table 2 Haze Relevant Features

Feature No.	Feature Name	Relation with Haze
$f1$	Brightness	Hazy image have large white pixels, such images have high brightness
$f2$	Dark Channel	Haze raises the intensity of dark channel and value of dark channel raises along with the amount of haze
$f3$	Chroma	Chroma is significantly correlated with haze
$f4$	Color Attenuation	It increases with the increase in concentration of haze.
$f5$	Colourfulness	Colorfulness is inversely proportional to haze.
$f6$	Color Gradient	Color Gradient is inversely proportional to haze.
$f7$	Color Variance	Variance diminishes eventually as haze intensity increases.
$f8$	Entropy	Entropy is inversely proportional to haze.
$f9$	Hue	Value of hue disparity decreases with the increase in haze.
$f10$	Luminance	Luminance is inversely proportional to haze.
$f11$	MContrast	Hazy image have low michelson contrast.
$f12$	Mean	Mean is inversely proportional to haze.
$f13$	MSCN	MSCN coefficients decreases as haze increase.
$f14$	MSE	Hazy image have low MSE contrast.
$f15$	Saturation	Saturation decreases sharply with the increase of haze
$f16$	Scene Depth	It increases alongwith haze.
$f17$	Sharpness	Sharpness is inversely proportional to haze.
$f18$	Weber Contrast	Hazy image have low weber contrast.
$f19$	Contrast Energy	Hazy image have low Contrast Energy

3.4 Deep Feature Extraction Using CNN

While physical haze priors capture low-level statistics, they cannot fully model the complex structural and semantic patterns introduced by haze. For this reason, we designed a lightweight Convolutional Neural Network (CNN) to extract complementary deep embeddings. The architecture is illustrated in Figure 3 and consists of the following components:

1. Input Layer: It accepts a resized RGB image of size 128X128X3 and normalize them to [0,1] to stabilize learning.

2. Convolutional Blocks (Feature Extraction):
   - Conv1: 32 filters of size 3X3, stride 1, ReLU activation.
   - Conv2: 64 filters of size 3X3, stride 1, followed by max-pooling (2X2).
   - Conv3: 128 filters of size 3X3, stride 1, followed by max-pooling (2X2).

   These progressively capture edges, textures, and mid-level haze patterns.
3. Flattening + Dense Layer (Embedding Space):
   The output is flattened and passed through a fully connected layer of 128 neurons with ReLU activation.This generates a 128-dimensional embedding vector, representing high-level haze-related features.
4. Dropout Regularization:
   A dropout layer (rate = 0.3) reduces overfitting, ensuring that embeddings generalize across scenes.
5. Feature Output:
   The 128-D embedding vector is extracted as the CNN feature representation.

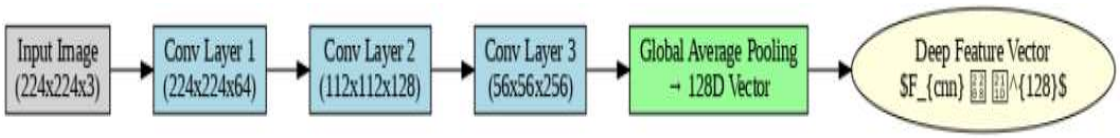


Fig. 3 CNN Feature Extraction Flow

3.5 Feature Fusion and Ensemble Model Training

The suggested Hybrid Haze Degree Estimation (HHDE) framework combines both physical features and deep features to create a complete feature representation of each image by merging the two types of features via a Convolutional Neural Network (CNN). This hybridization allows the model to learn together handcrafted haze-related attributes and deep semantic representation. Whereas the physical features provide interpretable image statistics including luminance and entropy, the CNN derived features provide high-level image characteristics including texture, edge sharpness, and spatial contrast. The presence of such complementing cues is a guarantee that the model is able to effectively employ low-level optical properties and high-level contextual signals relating to haze.

The hybrid feature vectors were formed after which the dataset was partitioned into training, validation, and testing subsets in a 60:20:20 ratio. The hybrid data was the input to the Random Forest (RF) and Extreme Gradient Boosting (XGBoost) as the base learners. Random Forest was selected due to its resistance to overfitting, multivariate and noisy data, as well as the inbuilt feature importance evaluation mechanism. By comparison, XGBoost is better at balancing bias-variance trade-off, offers more control over the model learning dynamics on a fine scale, and turns out to be very robust in imbalanced datasets. The combination of these models defines a variety

Algorithm 1 Hybrid Haze Degree Estimation using Stacked Ensemble

Require: Image dataset, physical features (F1--F19), haze labels
Ensure: Predicted haze degree with uncertainity

Preprocessing
Handle missing values in physical features (mean imputation)
Normalize image pixel values to [0, 1]
Resize all images to required CNN input size
Feature Extraction
Extract CNN feature vector of 128 dimensions
Extract 19D physical features
Concatenate both to form hybrid feature vector (147D)
Split Dataset
Perform train-validation-test split (60/20/20)
Assign X_{train}, X_{val}, X_{test}, y_{train}, y_{val}, y_{test}
Train Base Models
Train Random Forest Regressor on X_{train}
Train XGBoost Regressor on X_{train}
Meta-Learner Training
Collect predictions from RF and XGB (stacked features)
Train Bayesian Ridge Regression on stacked predictions
Construct Stacking Ensemble with passthrough
Evaluation
Predict haze degree on X_{val} and X_{test}
Compute R^2, MAE, RMSE for evaluation

of relationships in the feature space. The HHDE model uses the two level stacking ensemble structure to combine their complementary strengths. In this configuration RF and XGBoost are independently trained using the hybrid training data and their independent prediction on the training and testing data creates the meta-feature space of the second learning phase. The secondary feature space captures the unique decisions made by the base learners, which enables the model to take advantage of joint predictive behavior.

Bayesian Ridge Regression is an implementation of the meta-learner, which combines these first-level predictions into one refined prediction. The Bayesian Ridge Regression is also highly beneficial in the sense that it does not only provide a sound regression but also provides probabilistic estimates of the regression parameters. Through the use of posterior distributions, it facilitates the quantification of prediction uncertainty, which gives out confidence measures in addition to estimating the degree of haze. This design that is conscious of uncertainty proves particularly useful in actual haze detection tasks, in which it is essential to understand the level of trustworthiness in a particular prediction. As an example, in cases where haze estimates are of high uncertainty the system can automatically add the extra validation steps or image enhancement processes therefore assuring reliable and interpretable decision-making.

3.6 Uncertainty Modeling and Propagation in HHDE

The Bayesian Ridge Regression model defines a predictive distribution for the haze degree conditioned on the hybrid feature vector $\mathbf{f} \in \mathbb{R}^d$:

$$p(y \mid \mathbf{f}) = \mathcal{N}(\mu, \sigma^2) \tag{1}$$

where $\mu = \mathbf{w}^\top \mathbf{f}$ represents the predicted haze degree and σ^2 represents the predictive variance. The variance captures uncertainty arising from heterogeneous feature representations as well as estimation variability within the stacking framework.

Based on this predictive distribution,a confidence interval can be computed as:

$$\mu \pm z_{\alpha/2}\sigma \tag{2}$$

where $z_{\alpha/2}$ is the standard normal quantile associated with a confidence level of $100(1-\alpha)\%$. By doing so, this formulation enables the framework to propagate the uncertainty associated with feature extraction and ensemble regression to the ultimate prediction, thus facilitating statistically based confidence limits on degree estimates of the haze.

Filing in the point estimates and confidence intervals enhances the reliability and interpretability, especially in vision-based systems that are subject to dynamically changing atmospheric conditions.

4 Results

In order to test the effectiveness and credibility of the developed technique, a set of extensive experiments was performed with the use of the dataset mentioned in Table 1. The proposed model aims at predicting the degree of haze of an image using these hybrid features. To this, an ensemble model has been created with a stacking architecture where Random Forest and XGBoost were used as base regressors and Bayesian Ridge Regression as the meta-learner. In this way, the model can enjoy the advantages of the complementary power of the tree-based methods and Bayesian generalization.

4.1 Assessment Criteria

The experimental design of the current research is based on Intel(R) Core(TM) i5-8265U CPU with a frequency of 1.60GHz with a boost up to 1.80 GHz, 16GB of memory, and it was implemented in Python programming language.The performance of the suggested model was evaluated on the basis of three most well-known regression metrics:

4.1.1 Mean Absolute Error (MAE)

MAE represents the difference between the actual and the forecasted value of the sample value of the model.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y_i}| \tag{3}$$

4.1.2 Root Mean Squared Error (RMSE)

RMSE provides information on whether the model is stable or not by highlighting the bigger error.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y_i})^2} \tag{4}$$

As haze degree is represented as a normalized continuous scalar in the range [0, 1], MAE and RMSE are reported in normalized haze units and are therefore unitless.

4.1.3 Coefficient of Determination (R^2)

The value of R^2 indicates the performance of the model. Higher the R^2 value better the model.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y_i})^2}{\sum_{i=1}^{n}|\hat{y_i} - \hat{y_i}|^2} \tag{5}$$

4.2 Comparison Experiment

The proposed framework was compared with a number of selected baseline regression models, such as Linear Regression, Ridge Regression, Support Vector Regression (SVR), K-Nearest Neighbors (KNN), Gradient Boosted Decision Trees (GBDT), Random Forest, XGBoost, and LightGBM. All these models were trained and tested on the same dataset and configuration with 60% of data utilized in training ,20% in testing and 20% in validation .

Table 3 Performance comparison of different prediction models

Model Name	MAE	RMSE	R2
Proposed Model	0.020574	0.030067	0.952515
XGBoost	0.020961	0.030406	0.920758
LightGBM	0.024314	0.032991	0.906710
Random Forest	0.026455	0.037664	0 .878416
GBDT	0.035238	0.046400	0.815465
Regression	0.035346	0.046637	0.813581
Ridge	0.035981	0.047514	0.806499
KNN	0.033963	0.050253	0.783552
SVM	0.045793	0.055654	0.734523

Table 3 summarizes the results. The amount of 0.0206, 0.0301 and 0.9525 at the proposed stacking model gave the best results in terms of MAE, RMSE and R^2. Conversely, individual models such as SVM and KNN have a far lower accuracy

and error. Though the tree-based models such as the XGBoost and LightGBM show competitive results they nevertheless did not reach the accuracy of the ensemble.

Graphical visualization of performance was also applied in order to improve the interpretability. RMSE, MSE, and R^2 scores of all the models were plotted 4 which evidently indicates that the proposed model is the best.

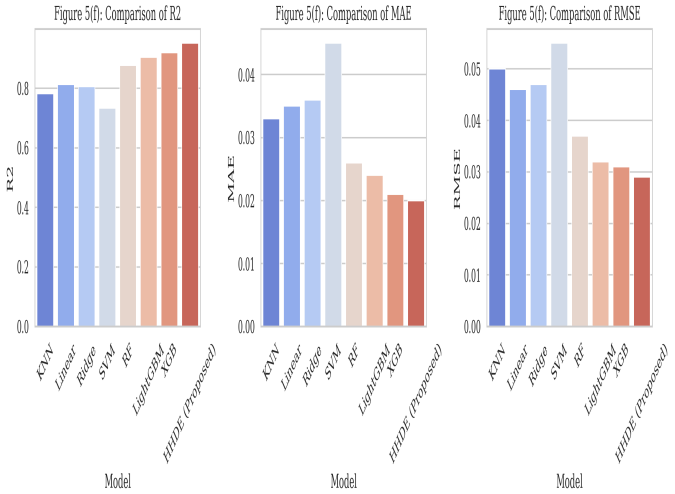


Fig. 4 Comparative results of R^2, MAE, and RMSE across baseline and proposed models

Generally, the findings show that the suggested hybrid ensemble system is a very precise and efficient tool in the prediction of haze level. It always performs better than the traditional machine learning models and even stronger individual learners through the use of ensemble diversity and deep integration of features. This renders the model very applicable in real world haze sensing and image-based environmental quality testing applications.

This paper also includes an ablation study and structural contribution analysis of the newly developed model with an objective to evaluate the contribution-margin of each part to the total value of the object-oriented system.

4.3 Ablation Study & Structural Contribution Analysis

In order to further determine the independent contribution of each of the key components in HHDE, we used a sequence of module-level ablation experiments. Such experiments are performed by methodically deleting or substituting certain architectural units to assess their respective effects on the feature extraction and fusion and computational efficiency. This method allows to better realize the effectiveness and necessity of each of the modules in the general system. To evaluate the contribution of each module, four configurations were analyzed:

1. Physical Features

2. Deep Features
3. Hybrid(RF+XGB without Bayesian layer)
4. HHDE (RF+XGB+Bayesian layer)

On these parts, we came up with four ablation variants which excluded or altered one or more modules, as shown in Table 4.

Table 4 Result of Ablation Experiment

Model Number	Physical features	Deep features	Hybrid	HHDE	MAE	RMSE	R^2
Ablation 1	✓	×	×	✓	0.0437	0.0675	0.8843
Ablation 2	×	✓	×	✓	0.0374	0.0609	0.9082
Ablation 3	✓	✓	✓	×	0.0298	0.0504	0.9347
Full Model	✓	✓	×	✓	0.0206	0.0301	0.9525

All the models were tested on the same data sets and training conditions. The key metrics of performance were chosen as MAE, RMSE, and the value of R^2, which offers the balanced evaluation. The entire HHDE model performs best with an R^2 of 0.9525 , RMSE of 0.0301 and MAE of 0.0206, as indicated by Table 4 hence confirming the suitability of the integrated modular design. The removal of individuals always leads to poor performance, and this proves that each of the modules is a positive contribution towards the capability of the model.

It is important to note that when the Bayesian Ridge Regression is eliminated in Ablation 3, the percentage of R^2 drastically drops to 0.9347, which is why this element is so important to the model to represent features and eliminate irrelevant information. A stronger degradation surface is in Ablation 1 with the lowest R^2 of 0.8843 %, the lowest MAE of 0.0437 and RMSE of 0.0675. Also, even when using Deep Features alone, as in Ablation 2, one obtains an R^2 0.9082, an MAE 0.0374, and an RMSE 0.0609. In general, the results of the ablation support the building reasons of HHDE and prove the need of its blocks.

5 Conclusion

This paper introduced an uncertainty-conscious Hybrid Haze Degree Estimation (HHDE) to overcome the shortcomings of exclusively physical and exclusively deep learning-based haze estimation methods. The given method proves to be effective in both low-level features of optical haze and high-level features of the scene related to atmospheric haze by combining both interpretable physical haze descriptors and CNN-based semantic embeddings into a stacking-based ensemble architecture.

The framework utilizes base learners, including Random Forest and XGBoost regressors, and employs a Bayesian Ridge meta-learner to combine their predictions through a probabilistic formulation. This design type not only enhances predictive

accuracy but also enables the explicit measurement of prediction uncertainty, which is crucial for the reliable decision-making process of safety-sensitive vision systems, such as UAV navigation, environmental monitoring, and autonomous perception.

Extensive tests on ten heterogeneous benchmark datasets demonstrate that HHDE consistently outperforms traditional regression models and robust ensemble baselines, achieving an MAE of 0.0206, RMSE of 0.0301, and R^2 of 0.9525. Ablation of these studies also demonstrates that both components, physical features, deep representations, and Bayesian stacking, are independent and synergistic in enhancing the performance of the entire system, confirming the proposed architecture's capability to be robust and generalize.

HHDE, in contrast to current deterministic haze estimation techniques, provides not only confidence independent predictions of haze degree, but also enables systems to determine the degree to which their results are reliable in uncertain weather conditions. This approach makes the suggested framework more suitable for real-world applications where environmental variability and noise cannot be avoided.

In the future, the proposed framework will be expanded to spatiotemporal haze estimation of video sequences, utilizing temporal consistency and dynamic scene modeling. Based on the need to enhance representational efficiency while being computationally feasible, lightweight transformer-based feature extractors will be incorporated. The method of inferential optimization will be investigated to enable its deployment on edge and embedded platforms in real-time. Moreover, uncertainty propagation will be modeled clearly at every step of the feature extraction pipeline, making it robust and reliable even in dynamic variations of outdoor conditions.

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