Temperature Prediction and Optimization of LCD Modules Using a Stacked Machine Learning Algorithm

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Abstract

High temperatures represent a significant failure risk in the display industry, especially for high-power LCD products, where thermal management plays a critical role in ensuring reliability and performance. The reliance on traditional FEA simulations, which generally take approximately one week during initial development stages, renders the thermal design and optimization of LCD modules a time-intensive and resource-intensive process, limiting efficiency and scalability. This study introduces a stacked machine learning algorithm designed to efficiently predict high-temperature risks in critical components of LCD modules. By leveraging the ensemble learning approach, the algorithm effectively addresses challenges in generalization and stability inherent to few-shot learning, achieving a MAE (mean absolute error) of 0.5°C in temperature prediction. Furthermore, it enhances simulation efficiency by more than 90% compared to traditional methods, providing a significant advancement in thermal analysis and design optimization. To enhance interpretability, SHAP-based explainable AI technique is used to identify critical factors influencing module temperatures and quantify the relationships between design parameters and maximum component temperatures. This methodology enables rapid evaluation of diverse design configurations, facilitates optimization beyond traditional experience-based approaches, and significantly mitigates the thermal failure risk in high-power MNT products.

Author Keywords

LCD Modules, Temperature, Machine Learning, Stacking Algorithms, Few-shot Learning, Rapid Evaluation.

1. Introduction

To meet the growing demand for superior image quality, the power consumption of LCD modules continues to increase, posing significant challenges for the thermal design of electronic components. Thermal management is a critical aspect of LCD module development, as excessive heat can negatively impact the lifespan and stability of display devices. High temperatures can lead to various issues, including material degradation, reduced lifespan, color shifts, and cracking at weld points. Statistics reveal that approximately 55% of electronic device failures are attributed to excessive heat [1]. If the heat generated by LED strips within the module is not effectively dissipated, it can decrease luminous efficiency, ultimately impairing display performance [2].

Controlling the temperature rise in LCD components is therefore imperative. During module design, particular emphasis should be placed on thermal management, making it a critical process in product development [3]. Traditional approaches to thermal design and optimization, such as FEA simulations and experimental methods, are often complex and fall short of delivering accurate and timely design results. To address this gap, many researchers have turned to AI techniques. For instance, Zhang et al. [4] applied single machine learning algorithms, including KNN, RF, and XGBoost, to address the color shift issue in Micro-LEDs under high-temperature conditions. Their approach achieved a single-pixel, single-color (R) brightness prediction accuracy of 1%, with similarly high accuracy for multi-pixel single-color (R) brightness predictions. Park et al. [5] utilized XAI models to predict temperature and power consumption in panels and modules under high brightness. Their results revealed a strong correlation between current density and panel heat generation, and they revisited previously overlooked areas outside the panel's center, uncovering their impact on thermal behavior. While these studies have advanced temperature prediction for LCD modules, their methods are not well-suited for thermal design when datasets are limited. This limitation is common in real-world scenarios, as generating sufficient datasets through FEA simulations and experiments is often challenging due to their complexity and time-intensive nature.

This paper proposes a stacked machine learning algorithm to predict the maximum temperature of LCD modules. First, FEA simulation is utilized to generate a comprehensive temperature dataset. The SPXY algorithm is then applied to split the dataset, ensuring that the training and validation subsets share the same underlying distribution. The training subset is used to develop the stacked machine learning model, while an independent test dataset is employed to evaluate its performance. Finally, the SHAP-based XAI technique is utilized to interpret the model and quantify the contributions of various features to the target value. These insights assist engineers in refining the design to effectively reduce the temperature of the LCD module.

2. AI Simulation Architecture

In previous extensive researches of MNT module temperatures, distinct stable temperature distribution patterns have been observed for direct-type and edge-lit modules. As shown in Figs. 1 and 2, the high-temperature regions in direct-type modules are concentrated in the upper-middle area, while in edge-lit modules, they are primarily located around the center of the light bar. In evaluating MNT module design, the primary concern is whether the peak temperature of critical components exceeds safety thresholds. Consequently, this paper emphasizes analyzing the distribution patterns of peak temperatures in the MNT modules.

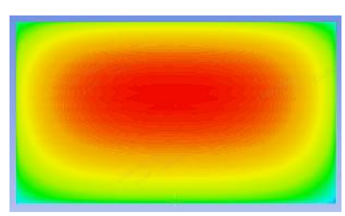

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Figure 1. Temperature distribution contour of direct-type module

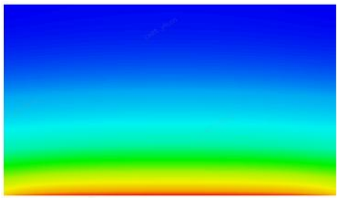

Figure 2. Temperature distribution contour of edge-lit module

Figure 3 illustrates the overall architecture for implementing an AI model to predict module temperature. Previous studies [6] have benchmarked the simulation model's accuracy, achieving FEA (finite element analysis) simulation-to-measurement error margins within ±3°C. Based on this high-precision simulation model, design parameters influencing module temperature are identified, and extensive FEA simulations are conducted to generate data for AI training based on DOE method. This process creates a high-quality dataset for training and assessing the AI model.

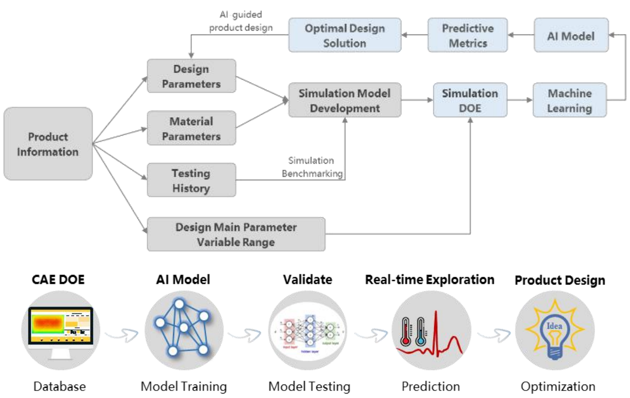

Figure 3. Overall architecture for implementing AI model

Based on previous experience with FEA simulations, the key factors influencing the temperature distribution of the MNT module are summarized in Table 1. Seventeen key factors have been identified for the four main temperature-sensitive components (OC, Film, LB, BC) of direct-type modules, while thirteen key factors have been identified for the corresponding components of edge-lit modules. To construct the dataset for AI model training, a total of 500 simulations for direct-type modules and 260 simulations for edge-lit modules were conducted using the DOE method.

Table 1. Key factors influencing the module's temperature

Design Parameters (Key Factor)			Predicted Component Temperature
Architecture	Model	21.5~34 inch	OC Film LB BC
	Type	Direct-type	
		Edge-lit	
LED	Encapsulation	COB/POB	
		Size	
	Chip	Size	
		Thermal power	
	Distribution	Pitch-X	
		Pitch-Y	
		Number	
Light Board/Bar	Material	thickness	
	Size	Thermal conductivity	
Backcover	Material	thickness	
	Size	Thermal conductivity	

3. Methodologies

(a) Dataset construction and sample division

The input features vary significantly in magnitude, spanning different orders, which can impede model convergence and diminish prediction accuracy. Therefore, Min-Max scaling is employed to normalize the input data, ensuring consistent feature ranges and enabling more effective model training. The formula for Min-Max scaling is provided Eq. 1:

$$\hat{x} = (x - x_{\min}) / (x_{\max} - x_{\min}) \tag{1}$$

where $\hat{x}$ represents the normalized value of the selected feature. $x_{\min}$ and $x_{\max}$ denote the minimum and maximum values of the feature in the raw input data, respectively.

Due to the limited dataset, a random division approach can result in training and test datasets having different distributions, making it challenging to effectively train and evaluate the model. To address this issue, the SPXY method is employed. This approach, an enhanced version of the Kennard-Stone algorithm, uses the maximum-minimum X-Y distance to ensure more representative and evenly distributed sample partitioning.

$$d_{xy}(p,q) = \frac{d_x(p,q)}{\max_{p,q} \in [1,N] d_x(p,q)} + \frac{d_y(p,q)}{\max_{p,q} \in [1,N] d_x(p,q)} \tag{2}$$

where x and y represent input features and target values, respectively. p and q are the indexes of two samples selected from the whole dataset with N samples, respectively. $d_x(p,q)$ or $d_y(p,q)$ is the Euclidean distance between pth and pth samples calculated from input values (x) or target values (y).

(b) Machine learning algorithm

In this research, an ensemble learning strategy is employed to address the common generalization challenges in few-shot learning[7]. Multiple weak machine learning models are combined as first-level models, or base models, including RF (Random Forest), GBR (Gradient Boosting Regressor), XGBoost, AdaBoost, LightGBM, SVM (Support Vector Machine), and others.

These first-level models are trained on the same dataset, and their predictions are fed into a higher-level model, such as Linear Regression, Kernel Ridge Regression (KRR), Lasso Regression, or similar algorithms, to generate the final prediction. This higher-level model, also referred to as the second-level model or meta-model, integrates the outputs of the base models to improve overall performance. The stacking architecture of the machine learning models is illustrated in Fig. 4.

The hyperparameters of the models are optimized using a Bayesian optimization algorithm, and eight-fold cross-validation is implemented to enhance the overall stability of the models. To evaluate the performance of the trained models, metrics such as MAE (Mean Absolute Error), RMSE (Root Mean Squared Error), and the R^2 (Coefficient of Determination) are employed.

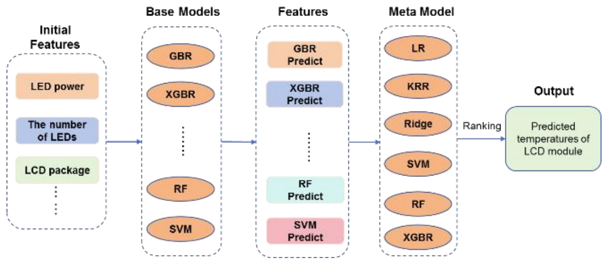

Figure 4. The stacking architecture of machine learning models developed for predicting the maximum temperatures of LCD components.

4. Results and Discussion

Experiments were initially conducted using various machine learning algorithms, including Gradient Boosting, XGBoost, Extra Trees, and Random Forest. The accuracy and stability of each model in predicting the temperatures of LCD components were assessed using eight-fold cross-validation, as shown in Table 2.

The results in Table 2 indicate that the XGBoost model outperformed the others in both accuracy and stability for temperature predictions, achieving an R^2 score of 0.983 and a standard deviation of 0.019. In contrast, the Random Forest model exhibited comparatively lower accuracy and stability, with an R^2 score of 0.947 and a standard deviation of 0.031.

Table 2. The accuracy and stability scores of different machine learning algorithms

Metric / Model	R2	MAE	RMSE
Gradient Boosting	0.976±0.033	0.987±1.242	3.544±4.195
Xgboost	0.983±0.019	0.847±0.918	2.973±2.831
ExtraTrees	0.983±0.022	0.880±1.066	3.206±3.527
Random Forest	0.947±0.031	2.592±1.579	5.355±3.347

To demystify the black-box nature of the machine learning algorithm, an XAI technique is employed to explain the model and identify the key factors contributing to temperature rise. Figure 5 presents the importance ranking of the top 8 features based on the mean SHAP values, evaluated using the XGBoost model. Since the SHAP analysis results for different temperature outputs are similar, only the results for the Y1 output are shown for brevity.

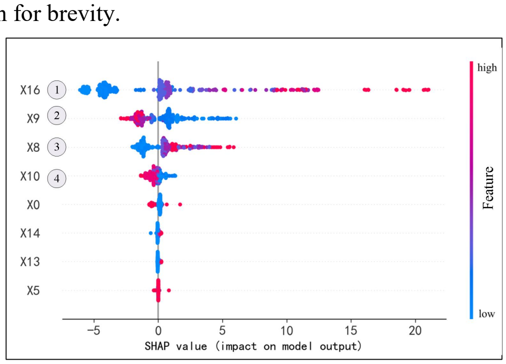

Figure 5. The importance ranking of the top 10 variables is determined based on the mean SHAP values, with the Y1 output used as an example.

From the figure, it is evident that features X16 , X9 , X10 and X8 are the top four factors influencing Y1 temperature rise. Specifically, X16 and X8 positively contribute to temperature rise, whereas X9 and X10 have a negative impact. These insights provide valuable guidance for adjusting parameters to optimize the design and ensure the LCD's maximum temperature remains within acceptable limits.

To enhance the accuracy and generalization of model predictions, a stacking strategy integrating multiple machine learning models is adopted. The algorithmic architecture of the stacking method is depicted in Fig. 4.

In the first layer, models such as Gradient Boosting, XGBoost, and Extra Trees are combined as base models, selected for their relatively high prediction accuracy. The output predictions from these first-layer models serve as input features for the meta-model in the second layer. The meta-model can be one of several algorithms, including Linear Regression, K-Nearest Regressor (KNR), Ridge Regression, XGBoost, SVR (with linear or RBF kernels), Lasso, or Gradient Boosting. A comparative analysis of these meta-models is presented in Table 3.

The results demonstrate that the stacking strategy significantly improves accuracy and stability compared to using a single machine learning algorithm. Among the meta-models, Gradient Boosting achieves the best performance, with the highest R^2 score and the lowest error in predicting maximum temperature, making it the optimal choice for the meta-learner. Specifically, the Gradient Boosting meta-model achieves an average R^2 score of 0.985 with a standard deviation of 0.023, while the SVR with RBF kernel yields an average R^2 score of 0.573 with a standard deviation of 0.164.

Table 3. The accuracy and stability scores of stacking machine learning algorithms

Metric / Meta Model	R2	MAE	RMSE
Linear Regression	0.983 ± 0.022	0.880 ± 1.066	3.206 ± 3.527
KNR	0.981 ± 0.025	0.888 ± 1.119	3.125 ± 3.515
Ridge	0.982 ± 0.023	0.879 ± 1.081	3.133 ± 3.589
Xgboost	0.969 ± 0.032	1.188 ± 1.386	4.005 ± 4.398
SVR_Linear	0.982 ± 0.023	0.890 ± 1.075	3.119 ± 3.545
SVR_RBF	0.573 ± 0.164	7.054 ± 4.880	19.22 ± 8.603
Lasso	0.976 ± 0.033	1.010 ± 1.254	3.550 ± 4.195
Gradient Boosting	0.985 ± 0.023	0.819 ± 1.142	2.745 ± 3.565

Figure 6 illustrates the performance of the Gradient Boosting meta-learner on Y1 temperature prediction, identified as the optimal model among various stacking architectures. The evaluation is conducted using a dataset of 53 samples, randomly selected from diverse regions of the data distribution to assess the model's prediction accuracy and generalization. Notably, the predicted Y1 values align closely with the ground truth, with errors remaining within ±0.9%, significantly below the required threshold.

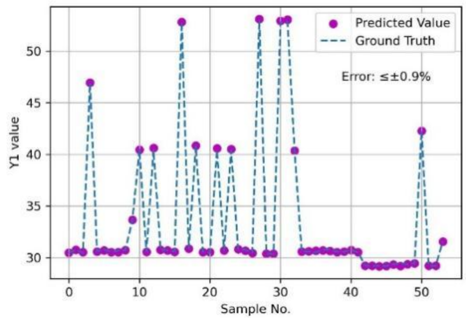

Figure 6. The plot of Y1 temperature predicted by Gradient Boosting meta-learner against the ground truth.

Figure 7 demonstrates the performance of the Gradient Boosting meta-learning model in predicting the Y4 target. The predicted maximum Y4 temperatures show excellent agreement with the ground truth. The evaluation metrics, including an R^2 score of 0.999, a Mean Absolute Error (MAE) of 0.5°, and a Root Mean Squared Error (RMSE) of 1.05°, all fall within the design specifications. For the sake of brevity, the results for other temperature outputs (Y2 and Y3) are not shown, as they exhibit similar performance to Y1 and Y4 .

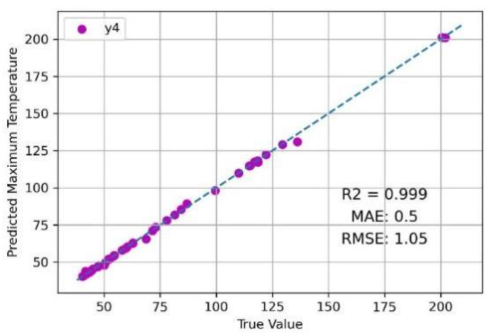

Figure 7. The prediction accuracy of the optimal stacking model, featuring the Gradient Boosting meta-learner, on Y4 temperature.

Based on this machine learning model, a complete evaluation software has been developed, which can quickly assess the highest temperature risk of modules in an offline environment, breaking the traditional simulation professional barriers.

This evaluation system has been applied to the temperature assessment of 27-inch MNT modules. After the collection of complete requirement information, there is no limit to the number of evaluation schemes that can be uploaded. For example, with one-click upload of 10 sets of evaluation schemes, the highest temperature prediction results under the conditions of each OC/Film/LB/BC scheme can be produced in about 1 minute, with the evaluation efficiency increased by more than 90%.

5. Conclusion

In summary, an AI model has been developed to improve the efficiency of designing LCD temperature components and to assist engineers in identifying the key factors affecting temperature distribution. Traditional FEA simulations are highly complex, and the available temperature datasets for LCD module design are often limited. Random splitting of the data can result in training and validation subsets that do not share the same underlying distributions. To address this issue, the SPXY algorithm is applied to calculate distances in the combined X and Y space, enabling the dataset to be partitioned in a way that maximizes diversity and representativeness in both training and validation subsets. This ensures the resulting subsets are well-suited for building models with robust generalization capabilities.

Subsequently, conventional machine learning algorithms, including XGBoost, Gradient Boosting, and Random Forest, are employed to predict the maximum temperatures of MNT components. Bayesian optimization is utilized to tune the hyperparameters of these models. Among the tested models, XGBoost demonstrates relatively satisfactory prediction performance. To further improve the model's accuracy and generalization, a stacking ensemble learning approach is employed. With Gradient Boosting as the meta-learner, the model demonstrates superior accuracy and minimal standard deviation compared to other approaches. For the Y4 temperature target, the prediction metrics, $R^2 = 0.999$, MAE = 0.5°C, and RMSE = 1.05°C, are comfortably within the required thresholds.

Additionally, the AI prediction model has achieved similarly high performance in other target predictions, with an improvement in evaluation efficiency of over 90%, significantly enhancing the efficiency of identifying temperature risks in MNT products during the early stages of product development.

6. References

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