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# Mean Radiant Temperature Modeling Using Deep Learning

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## INTRODUCTION

Outdoor thermal comfort is a critical determinant of urban livability, particularly in desert climates where extreme heat poses challenges for public health, energy consumption, and urban planning. Mean Radiant Temperature (MRT) plays a pivotal role in evaluating outdoor comfort as it integrates the effects of shortwave and longwave thermal radiation on the human body. In this work, we extend the predictive modeling of MRT by integrating Neural Networks (NNs) and Physics Inforrmed Neural Networks (PINNs) into the prediction pipeline. Building on the MaRTy dataset, which contains high-resolution environmental measurements along with the images, our approach moves beyond the machine learning methods such as kernel-based and tree-based predictors to extract the rich features from the images and incorporate them to the predictive model. These features are extracted from fisheye images using a deep learning architecture, enhancing prediction accuracy while requiring fewer sensor inputs. This advancement is aimed at creating scalable and generalizable solutions for urban planners to assess outdoor thermal comfort.

## METHODS

- Neural Network Framework: To predict MRT, we employ a Physics-Informed Neural Network (PINN) framework. This network incorporates both metadata (e.g., air temperature, wind speed, solar altitude) and fisheye image features, captured through a pretrained ResNet-50 backbone, which we fine-tune by unfreezing the last 30 layers. The network predicts shortwave and longwave radiation components, subsequently used to calculate MRT via a physics-based loss function.

Loss Function: The PINN's loss function integrates the physical relationships governing MRT prediction:

$$MRT = \frac{1}{a_1\sigma}\left[W_{up-down}\sum_{i\in\{up,down\}}(a_kS_i + a_lL_i) + W_{others}\sum_{i\in\{north,south,east,west\}}(a_kS_i + a_lL_i)\right]^{0.25} - 273.15$$

*Where $S$ and $L$ represent shortwave and longwave radiation, and $W$ coefficients are weighting factors for vertical and horizontal directions, and $a_k$ and $a_l$ are absorption coefficients for shortwave and longwave radiation and σ is Stefan-Boltzmann constant.*

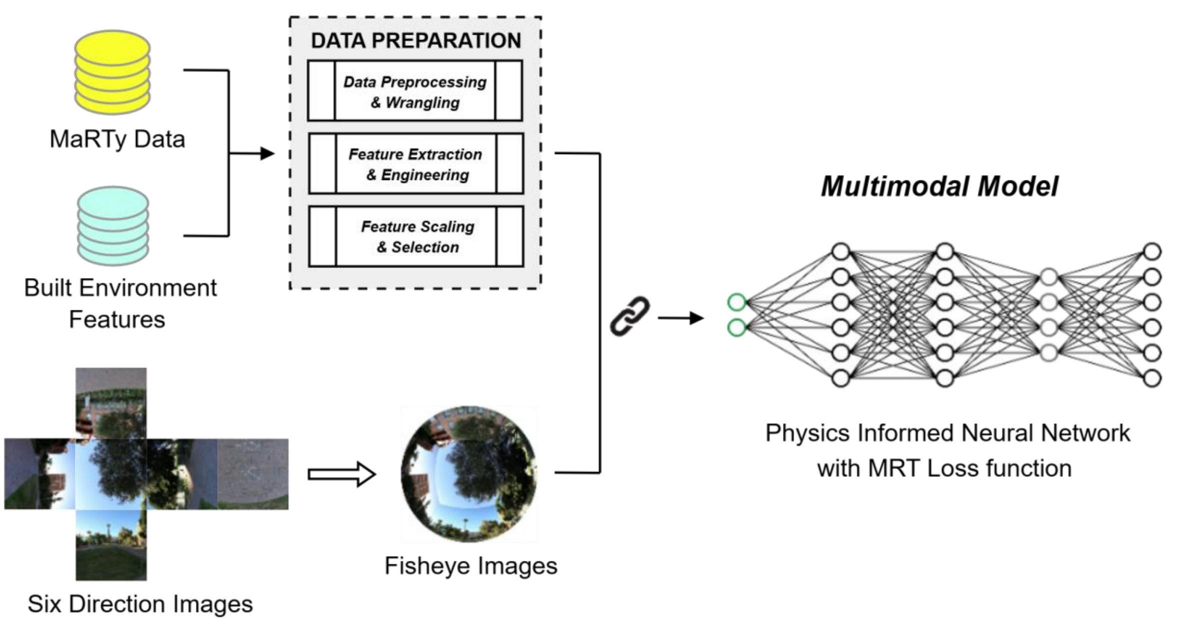


**Figure 1**. Summary of data and workflow

- We conducted an ablation study to evaluate the impact of different features on neural network performance. Starting with the comprehensive feature set from WebMRT, we sequentially removed the shade feature and then the built environment features (surrounding trees, buildings, and impervious surfaces) to assess their significance. We then enhanced the models by incorporating fisheye images processed through a pretrained ResNet-50 backbone, fine-tuning its last 30 layers for optimal feature extraction. Finally, we implemented a Physics-Informed Neural Network (PINN) and systematically tested the feature configurations again, demonstrating the combined contributions of metadata and image features to MRT prediction.

## RESULTS

Performance comparison of different machine learning models using the feature sets worked with in WebMRT, derived from related prior work. The feature set includes air temperature, relative humidity, wind speed, altitude above sea level, presence of shade at measurement, sky view factor upward, percentage of surrounding trees, percentage of surrounding buildings, percentage of impervious surfaces, time in minutes from sunrise, angle of the sun's azimuth, and angle of the sun's altitude. This analysis highlights the effectiveness of different models in predicting MRT using these comprehensive features (Table 1).

| Model | RMSE | $R^2$ | Features |
|---|---|---|---|
| Ridge Regression | 5.43 | 0.782 | WebMRT Set |
| Lasso Regression | 5.50 | 0.777 | WebMRT Set |
| SVR | 3.96 | 0.884 | WebMRT Set |
| Decision Tree | 4.71 | 0.836 | WebMRT Set |
| Random Forest | 3.45 | 0.902 | WebMRT Set |
| LightGBM | 3.44 | 0.910 | WebMRT Set |
| XGBoost | 3.43 | 0.913 | WebMRT Set |

Our results demonstrate that the proposed PINN framework outperforms the prior methods and tree-based models as well. The integration of fisheye images and fine-tuning the ResNet significantly enhances the model's capacity to capture image features, resulting in improved prediction accuracy for shortwave and longwave radiation components (Table 2).

**Table 2.** Deep learning models performance

| Model | RMSE | $R^2$ | Features | Images |
|---|---|---|---|---|
| Neural Network | 7.83 | 0.832 | WebMRT Set | ✗ |
| Neural Network | 19.54 | 0.694 | Shade ✗, Built Environment ✗ | ✗ |
| Neural Network | 13.35 | 0.745 | Shade ✗, Built Environment ✓ | ✗ |
| Neural Network | 6.06 | 0.853 | Shade ✗, Built Environment ✗ | ✓ |
| PINN | 7.76 | 0.846 | WebMRT Set | ✗ |
| PINN | 10.81 | 0.758 | Shade ✗, Built Environment ✗ | ✓ |
| PINN | 15.57 | 0.721 | Shade ✗, Built Environment ✗ | ✗ |
| PINN | 6.04 | 0.867 | Shade ✗, Built Environment ✓ | ✓ |
| PINN fine-tuned | 4.61 | 0.891 | Shade ✗, Built Environment ✗ | ✓ |

Comparison of model performance based on RMSE values over 50 training epochs. The models include various configurations of neural networks and Physics-Informed Neural Networks, with and without image inputs and fine-tuning.

Some models exhibit smoother convergence trends, while others demonstrate noisier behavior, reflecting potential instability during training. The best-performing model, "PINN with Images and Fine-tuned ResNet," achieves the lowest RMSE through consistent refinement and convergence.

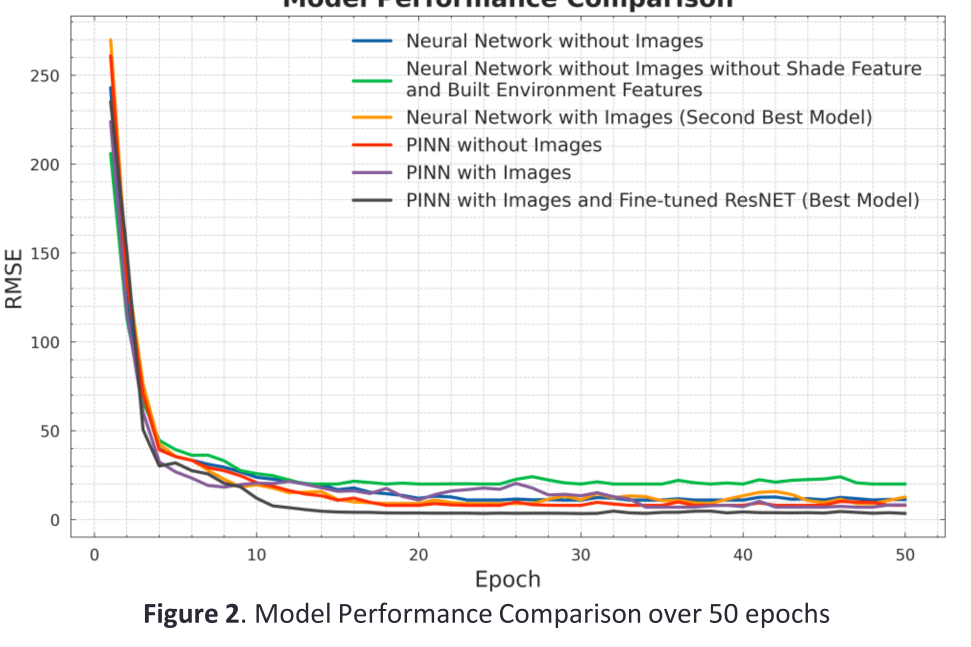


**Figure 2**. Model Performance Comparison over 50 epochs

## FUTURE WORKS

The next steps include:

- Further optimizing the PINN architecture for computational efficiency.
- Exploring alternative deep learning architectures for fisheye image analysis.
- Perform segmentation on fisheye images using a neural network to extract built environment features dynamically and integrate these features into the predictive framework to enhance model performance.

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