Thermal Imaging Analysis

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Abstract

This research explores the application of thermal imaging technology to assess energy efficiency and structural performance in buildings on Loyola University Chicago's Lakeshore Campus. Specifically, the analysis focuses on the thermal dynamics of windows in Dumbach Hall and Cuneo Hall. By employing advanced imaging techniques, data logging, and analytics, the study identifies key heat anomalies, assesses insulation inefficiencies, and evaluates areas prone to energy loss. The integration of a custom-built data registry and a Power BI dashboard

underscores the utility of data science tools in energy audits. These results inform actionable strategies for improved energy management and building maintenance.

Introduction

Buildings are responsible for a significant portion of global energy consumption, with windows often being the weakest points in thermal insulation. Heat loss or gain through windows can drastically impact energy efficiency, resulting in increased heating or cooling costs and a larger environmental footprint. Understanding the dynamics of heat transfer through windows is crucial for optimizing energy use, improving structural integrity, and supporting sustainability goals. This study focuses on utilizing thermal imaging technology to identify, analyze, and visualize heat transfer patterns on the windows of two prominent buildings at Loyola University Chicago's Lakeshore Campus: Dumbach Hall and Cuneo Hall.

Thermal imaging is a non-invasive and effective method for detecting temperature anomalies, such as areas of heat leakage or inefficient insulation. This method captures variations in surface temperatures and provides insights into potential structural weaknesses. By analyzing these patterns, we aim to uncover actionable insights that can guide energy-efficient building practices and reduce energy waste.

The primary goals of this study are:

1. **Detection of Heat Anomalies**: Utilizing thermal imaging technology to capture temperature variations on building windows and identify potential problem areas.
2. **Systematic Data Logging**: Developing a structured approach for recording observations to ensure consistent and replicable data collection.
3. **Statistical and Visual Analysis**: Employing advanced data science techniques to extract meaningful patterns and trends from the data.

The study integrates a multidisciplinary approach, combining fieldwork, data management, and advanced analytics. On-site thermal imaging was complemented by the development of a web-based platform, the *Loyola Thermal Image Registry*, for efficient data logging and management. Furthermore, a dynamic Power BI dashboard was created to visualize the data and communicate findings effectively. Statistical techniques were applied to validate observations and uncover correlations between environmental and structural factors.

This research also explores broader implications, such as enhancing energy efficiency, reducing maintenance costs, and contributing to sustainable infrastructure management. By identifying areas of improvement, this study provides actionable recommendations for maintaining energy-efficient buildings and highlights the potential for similar applications in other environments.

The project is innovative in its use of data science and technology to address practical challenges in building management. It serves as a replicable framework for thermal analysis and establishes a foundation for future studies in sustainable infrastructure. Through this research, we aim to contribute to Loyola University Chicago's commitment to environmental sustainability and energy efficiency, setting an example for academic institutions worldwide.

Methodology

The methodology for this project was designed to systematically capture, manage, and analyze thermal imaging data to uncover meaningful insights about heat transfer patterns in the windows of Loyola University Chicago's Dumbach Hall and Cuneo Hall. The process involved four key stages: data collection, data management, data visualization, and statistical analysis. Each stage was tailored to ensure high-quality data acquisition, efficient handling, and insightful analysis.

Data Collection

The first stage of the project involved on-site data collection using a HIKMICRO E1L thermal camera, capable of capturing detailed temperature variations in JPEG format. This camera records temperature data as pixel values, embedded with EXIF metadata (e.g., timestamp, GPS coordinates). Thermal images were taken under controlled conditions, accounting for time of day, weather, and sun exposure.

Key data points recorded during this stage included:

- **Location Information**: Latitude and longitude of observation points were captured to map thermal anomalies spatially.
- **Temperature Metrics**: Minimum, maximum, and observed temperatures for each window provided a range of heat readings.
- **Environmental Conditions**: Factors such as outdoor temperature, sun direction, and time of day were documented to contextualize the heat patterns observed.
- **Framing and Context**: Observations regarding framing conditions, building side (e.g., north, south), and distance from the subject were noted to ensure a holistic analysis.

The data collection process involved systematic recording of thermal images across both buildings. Multiple images were captured for each window at different times to analyze temporal patterns and variations in heat distribution.

Data Management

To handle the vast amount of collected data, a custom-built web application called the *Loyola Thermal Image Registry* was developed. This platform served as a centralized repository for logging, storing, and exporting the data, ensuring that it remained organized and accessible for analysis.

Key features of the application included:

- **Log Form**: A structured interface allows users to input data such as building name, coordinates, temperatures, and environmental conditions. The form was designed to minimize errors and ensure consistent recording.
- **Data Registry Table**: All logged data was displayed in a searchable and sortable table, enabling users to view and edit entries as needed. This facilitated quick access to specific observations and provided a comprehensive overview of the dataset.
- **Export Capabilities**: To support further analysis, the application enabled exporting data to formats such as CSV, compatible with statistical and visualization tools like R, Python, and Power BI.

The application also incorporated standardization features, ensuring that all entries followed a consistent format, which was critical for subsequent analysis and comparisons.

Data Visualization

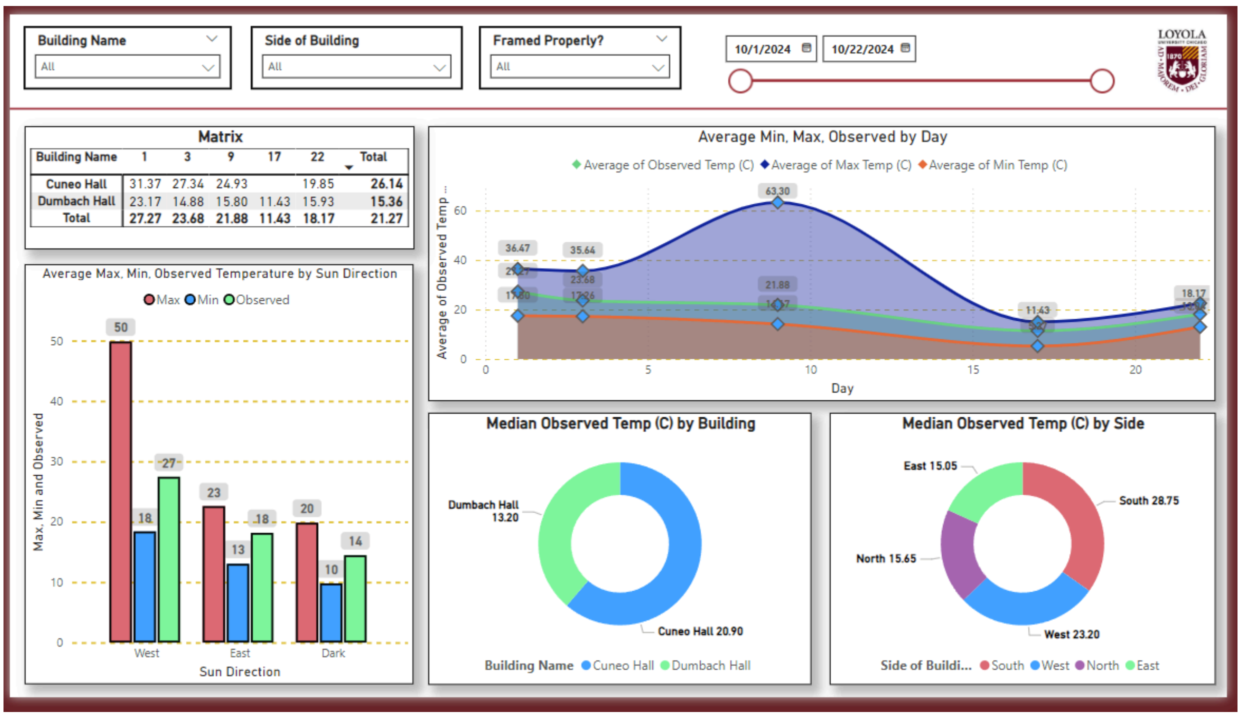
To transform raw data into meaningful insights, a dynamic Power BI dashboard was developed. This dashboard provided an interactive and visually engaging way to explore the data, highlighting trends, anomalies, and correlations. The dashboard's key components included:

1. **Dynamic Filters**: Users could filter data based on building, side of the building, framing conditions, and time range. This allowed for focused analysis and comparisons.
2. **Graphical Representations**:

- **Line Graphs**: Illustrated daily trends in observed, maximum, and minimum temperatures.
- **Bar Charts**: Compared heat anomalies by sun direction, building, and framing condition.
- **Heat Maps**: Highlighted spatial temperature distributions, making it easy to identify areas of concern.

3. **Summary Statistics**: Pie charts and matrices summarized key metrics such as median temperatures by building and side, offering a quick overview of the findings.

The dashboard served not only as an analytical tool but also as a medium for presenting findings to stakeholders in an easily digestible format.



Statistical Analysis

To complement visual analysis, rigorous statistical methods were applied to uncover deeper insights from the data and validate findings. The statistical analysis was conducted using tools like R and Python and involved the following steps:

1. **Descriptive Statistics**:
    - Calculated measures of central tendency (mean, median) and variability (standard deviation, range) for observed temperatures.
    - Summarized key trends in heat anomalies across different buildings and environmental conditions.

2. **Inferential Analysis**:
    - **Correlation Analysis**: Explored the relationship between observed temperatures and environmental factors such as sun direction and outdoor temperature.
    - **Hypothesis Testing**: Conducted t-tests and ANOVA to determine significant differences in temperature patterns based on building and side.
3. **Comparative Analysis**:
    - Compared temperature variations between buildings to assess the impact of structural and material differences.
    - Analyzed framing conditions to identify their influence on heat retention.
4. **Temporal Analysis**:
    - Studied patterns over time to identify peak heat loss periods and their potential causes.

These statistical techniques provided robust evidence to support the visual findings, ensuring that the conclusions drawn were both accurate and scientifically sound.

Image Processing and Machine Learning Approaches

To enhance the analysis of thermal imaging data, advanced image processing techniques and exploratory machine learning methods were implemented. These approaches aimed to extract meaningful features from the thermal images, correlating them with metadata from the log data for deeper insights.

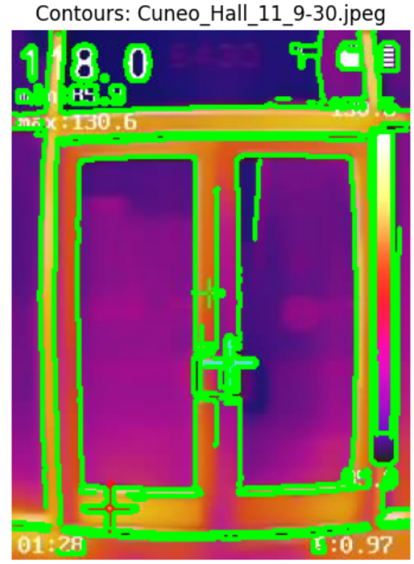
Image Processing

Image processing played a pivotal role in this study, serving as a critical step in identifying thermal patterns, isolating areas of interest, and preparing the images for comprehensive analysis. Each processing step was designed to enhance the raw thermal data, allowing for clearer visual interpretation and more accurate analytical outcomes.

Contour Detection

The initial step in processing was the application of contour detection using OpenCV. Contour detection allowed the identification and outlining of significant temperature anomalies within the images. These anomalies were often observed around window edges or improperly sealed frames, areas known for potential heat leakage. By highlighting these regions, contour detection provided a visual roadmap for focused analysis, making it easier to isolate problematic zones for further investigation.

Contours: Cuneo_Hall_11_9-30.jpeg



Histogram Equalization

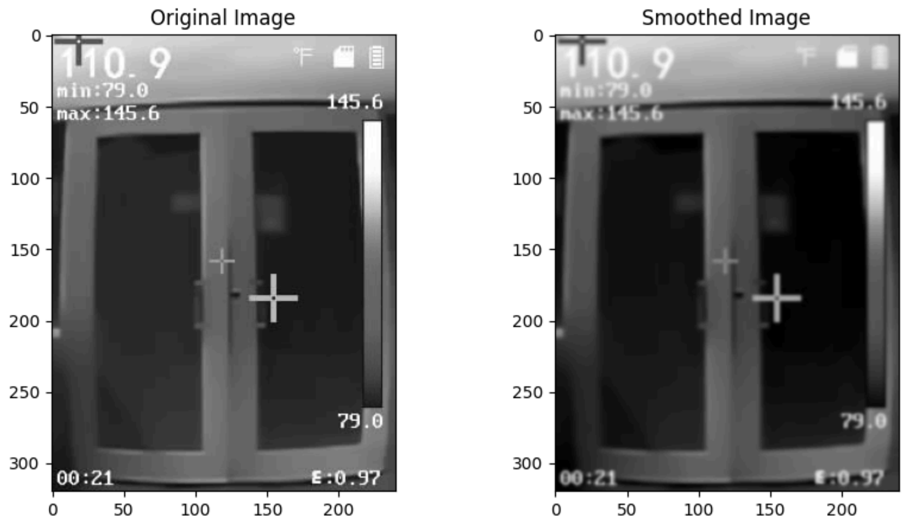
To enhance the visibility of subtle temperature variations, histogram equalization was applied to the grayscale versions of the thermal images. This technique redistributed pixel intensity values across the available range, resulting in a more even contrast and emphasizing temperature gradients. For example, temperature shifts that were previously indistinguishable became more apparent, enabling researchers to detect fine details in heat distribution. This step was particularly effective in identifying low-contrast anomalies that might otherwise go unnoticed.

Region of Interest (ROI) Segmentation

Regions of interest (ROIs), such as window surfaces, were segmented from the broader image using a combination of manual and automated techniques. By isolating these ROIs, irrelevant areas like walls, doors, or surrounding structures were excluded from the analysis. This targeted approach reduced noise and ensured that only meaningful data contributed to subsequent analyses.

Noise Reduction

Thermal images often contain random variations in pixel intensity, commonly referred to as noise. Noise can distort the analysis by introducing artifacts that do not reflect actual thermal patterns. Gaussian blurring was employed to mitigate this issue. This smoothing technique softened abrupt changes in pixel intensity, effectively removing high-frequency noise while preserving critical edges and contours. The result was a cleaner dataset, free from extraneous distortions, and ready for deeper analysis.



Challenges & Refinements

During the image processing phase, certain challenges were encountered, including variations in lighting conditions and environmental noise that impacted image clarity. For instance:

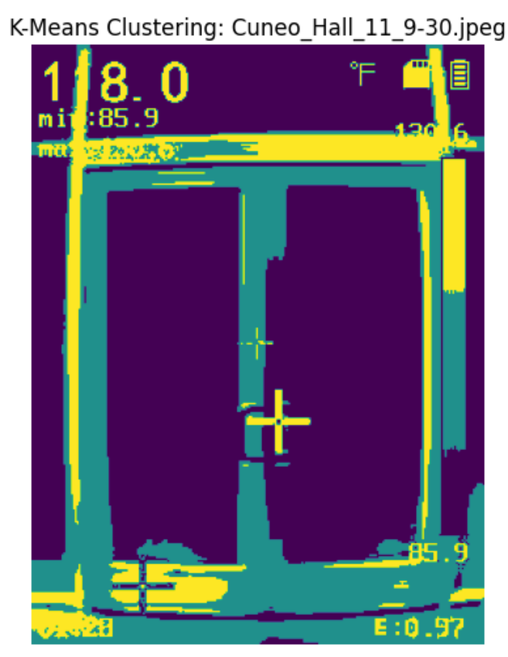
- Thermal images taken during different times of the day exhibited varying contrast levels, necessitating adjustments in histogram equalization parameters.
- Overlapping objects near windows introduced complexity in contour detection, requiring additional preprocessing steps to filter out irrelevant contours.
- The thermal images contained unavoidable noise, which was detected as noise when using various techniques such as contour detection and ROI segmentation. This would need to be tackled to avoid skewed results.

Despite these challenges, iterative refinements in the processing pipeline, such as fine-tuning blurring and segmentation techniques, successfully addressed these issues. The result was a robust processing workflow capable of handling diverse image conditions.

Future Directions for Image Processing

Building on the success of these methods, future iterations of the project could incorporate advanced image processing techniques, such as:

- **K-Means Clustering**: To segment thermal images into distinct temperature zones automatically.
- **Edge Detection Algorithms**: To refine the accuracy of ROI boundaries and improve the precision of contour identification.



- **Deep Learning-Based Processing**: Leveraging convolutional neural networks to enhance automatic feature extraction and anomaly detection.

By continuing to refine and expand image processing techniques, this study can further improve the accuracy and efficiency of thermal analysis, ensuring actionable insights for building maintenance and energy efficiency.

Machine Learning Opportunities

In terms of utilizing thermal images in the context of machine learning, significant number of opportunities arise in these following areas:

- **Feature Extraction:**
  - Machine learning models can be employed to analyze pixel intensity distributions and temperature gradients from the images. Furthermore, certain other features can include the characteristics of a window, or door for classification purposes. These features can serve as possible predictors for tasks such as identifying heat losses, water leaks, and assessing insulation.
- **Classification Tasks:**
  - Through the use of supervised learning, labeling the images as [Good insulation vs Poor insulation] can be efficiently utilized to classify new images of the predefined categories. Through the use of Convolutional Neural Networks (CNNs) are highly suitable for these tasks due to their translation invariant and spatial hierarchies learning characteristics.
- **Predictive Analytics:**
  - Regression models could be utilized to predict quantitative outcomes, such as the rate of energy loss or the size of a potential water leak that was detected. These are often utilized with the metadata stored in the images, unfortunately are not found in the current camera used in this project.

Thermal Image Classification for windows and doors

In this section, we focus on building a convolutional neural network (CNN) for classifying thermal images, specifically targeting windows and doors. While our initial goal was to explore broader image classification objectives, the limited variety of images, such as those depicting leaky or poorly insulated windows and doors, narrows our approach.

However, this limitation also presents an opportunity to explore more focused tasks and lay the groundwork for future advancements.

Objective:
Our primary goal is to classify thermal images into two categories: Windows and Doors. By doing so, we aim to develop a robust foundation for future work in thermal image analysis.

As we progress, this model can be expanded to more complex classifications, such as identifying leaky or poorly insulated areas, ultimately contributing to energy efficiency assessments and building inspections.

Image Cleaning:

- **Crosshairs:** Although helpful in targeting specific points in an image for the user. This would need to be cleaned out, as issues arise during image processing.
- **Temperature Readings/Labels:** Several annotations and temperature values displayed in certain areas of the image may interfere with model training.
- **Machine Learning Challenges:** The presence of these crosshairs and labels, may impact the image classification model to focus on these non-representative features rather than the actual thermal patterns that matters. This may reduce the model's ability to generalize, leading to a lower accuracy, performance and a higher loss.

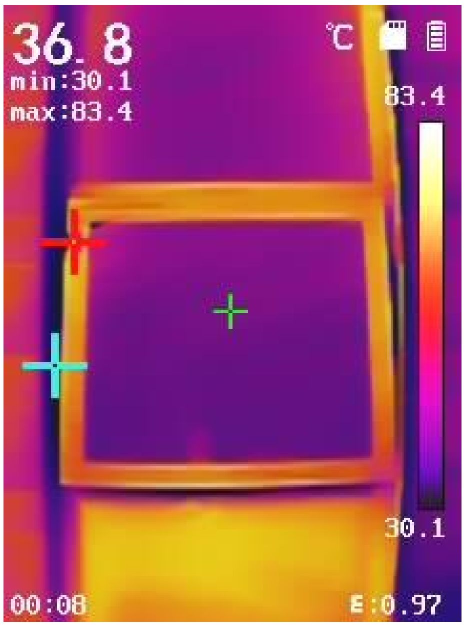
Possible solutions:

- **Alignment & Distance:** Prior predetermined distance and alignment before taking a photo, may help. As cropping is a possibility in order to remove certain parts, however the crosshairs will still remain to be visible.
- **PicWish:** An AI image cleaning app that is often used to remove text from an image. This proved to be a much more efficient and less-costly method. Furthermore, it reduces the possibility of altering or damaging the images.
- **Different Camera:** Possible use of different thermal heat cameras, in which the user may have more control over the output of the image. For instance, ability to only capture an image without overlays.

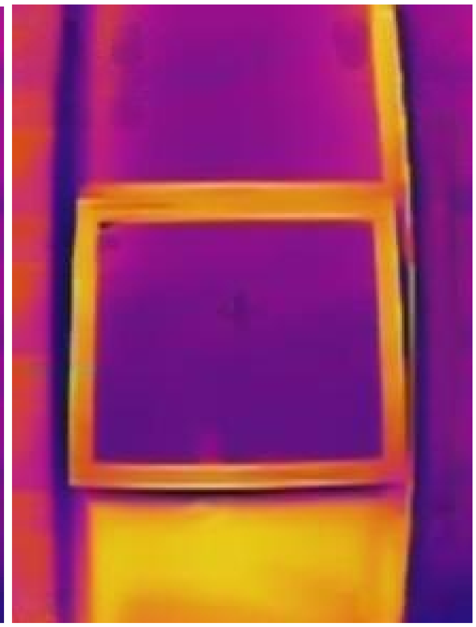
Image Processing

Through the use of PicWish, an AI photo editor primarily used to remove text from any photos, we are able to remove overlays present on a photo. This is primarily done in order for the model to pick up on important features such as edges and lines present on the windows and doors. However with these overlays as stated before, it may impact our model's performance in extracting the important features and not the overlays. In the photos below, the ‘before’ and ‘after’ images demonstrate the effectiveness of the cleaning process. The ‘after’ image retains the original characteristics of the ‘before’ image, indicating that the cleaning process has preserved the integrity of the subject without introducing any alterations.

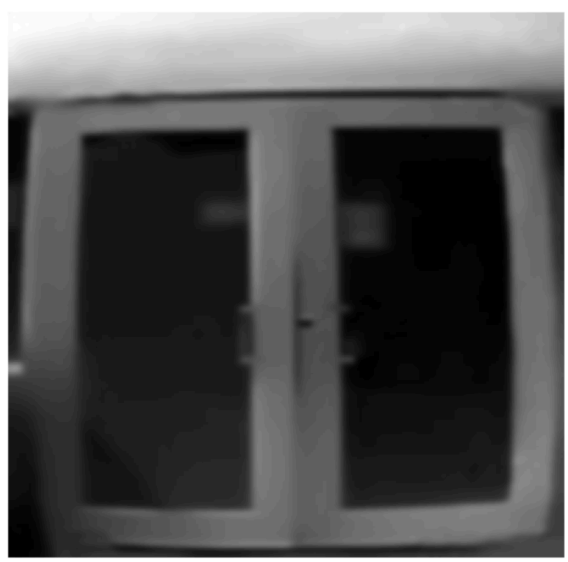
Before



After



After cleaning the images, we then apply a smoothing function, by applying gaussian blur to minimize any noise present within the photos. The images are then resized and converted to grayscale to standardize the input for model analysis. This processing method has significantly contributed to improving the model’s performance by ensuring cleaner and more uniform data.



Data labeling & Split

The data is then carefully labeled to ensure each image is accurately categorized based on our objectives. In this case, the windows are labeled 1 and the doors are labeled 0. Following this, the dataset is then split into a training set and a testing set, typically the range is 80/20, or 70/30, in this case 80/20.

Model Architecture:

The model architecture consisted of several convolutional layers to extract spatial features from the thermal images, followed by dense layers for classification. Key layers included:

- **Convolutional Layers:** Extracted feature maps to identify patterns such as edge, shapes, and key characteristics that differentiate doors and windows.
- **Pooling Layers:** Reduced spatial dimensions to optimize computational efficiencies, and discarding unimportant parts of the photos.
- **Dropout Layers:** Prevented overfitting by randomly deactivating neurons during training.
- **Dense Layers:** Acted as the classifier, with the final output being a single neuron with a sigmoid activation function for binary classification.

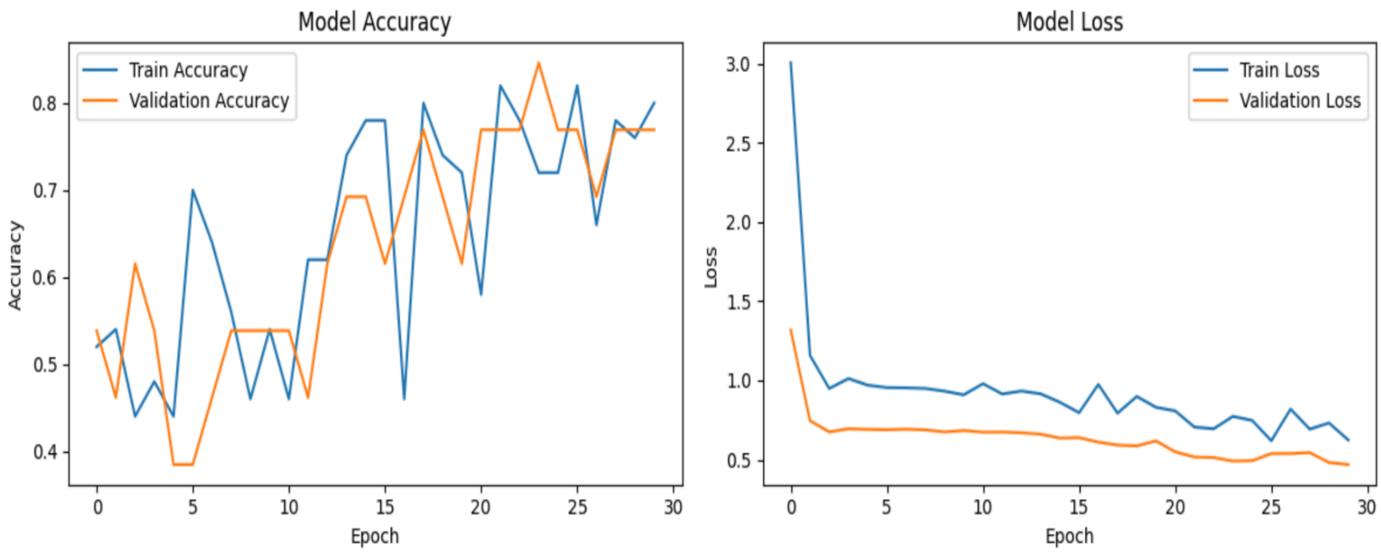
Model Architecture

Model: "sequential_10"

Layer (type)	Output Shape	Param #
conv2d_20 (Conv2D)	(None, 222, 222, 32)	320
max_pooling2d_20 (MaxPooling2D)	(None, 111, 111, 32)	0
conv2d_21 (Conv2D)	(None, 109, 109, 64)	18,496
max_pooling2d_21 (MaxPooling2D)	(None, 54, 54, 64)	0
flatten_10 (Flatten)	(None, 186624)	0
dense_20 (Dense)	(None, 128)	23,888,000
dropout_10 (Dropout)	(None, 128)	0
dense_21 (Dense)	(None, 2)	258

Total params: 71,721,224 (273.59 MB)
Trainable params: 23,907,074 (91.20 MB)
Non-trainable params: 0 (0.00 B)
Optimizer params: 47,814,150 (182.40 MB)

Model Results

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Validation Accuracy: 76.92%
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 321ms/step

Classification Report:
              precision    recall  f1-score   support

       Doors       0.80      0.67      0.73         6
     Windows       0.75      0.86      0.80         7

    accuracy                           0.77        13
   macro avg       0.78      0.76      0.76        13
weighted avg       0.77      0.77      0.77        13
```

Final Results
The final results of the training session describes the process of the model trained over 30 epochs with a batch size of 8, and an initial learning rate of 0.006.

- Initial Training: The accuracy starts at 51.78% in the first epoch and improves steadily, in which later the learning rate reduces. This is due the validation loss flatlining, this allows the model to adjust the learning rate to stabilize the accuracies.
- Final performance: By the end of training, the model achieves a validation accuracy of 76.92% with a test loss of 0.4693, this can further be seen in the plots.

- Overall Accuracy: 77% with the weighted average of precision, recall, and F1-score achieving 0.77.

Overall, this model is a foundational step towards classifying images based on key characteristics like leaks or insulation, as this showcases the endless possibilities. However, certain issues are encountered, primarily due to the number of thermal images available, in which image classification will surely struggle with. Nonetheless, increasing the number of images will surely improve the model's convergence, performances and accuracy.

Thermal Analysis of Building Envelopes: A Comparative Study of Cuneo Hall and Dumbach Hall

Analysis Methodology

The analysis focused on thermal imaging data collected from two campus buildings: Cuneo Hall and Dumbach Hall. We developed a comprehensive understanding of each building's thermal performance through a systematic processing of thermal images, combined with environmental data logging.

Each thermal image underwent a four-stage processing methodology. Starting with grayscale conversion, the process defined specific regions of interest by separating the outer frame from the central area. These grayscale values were then mapped to actual temperature ranges recorded during image capture. Finally, mean temperatures were calculated for different regions, enabling detailed thermal analysis.

Key Performance Metrics

Two primary metrics were developed to quantify thermal performance:

- The Heat Loss Index (HLI) measures the magnitude of heat transfer, calculated using temperature differentials normalized by standard deviation. This provides a scale from 0 to 1+, where lower values indicate better thermal performance. Values exceeding 1.0 signify areas requiring immediate attention.

- The Insulation Effectiveness Score (IES) evaluates overall insulation performance on a percentage scale. This metric considers the ratio of actual temperature differential to the maximum possible temperature range, with scores above 90% indicating satisfactory performance.

Analysis Results

Overall Building Performance

The analysis revealed subtle but meaningful differences between the two buildings. Cuneo Hall demonstrated slightly superior thermal performance with an average Heat Loss Index of 0.23 and an Insulation Score of 94.4%. In comparison, Dumbach Hall showed an average HLI of 0.27 and an Insulation Score of 92.0%. However, statistical analysis yielded a p-value of 0.1413, indicating that these differences, while notable, are not statistically significant

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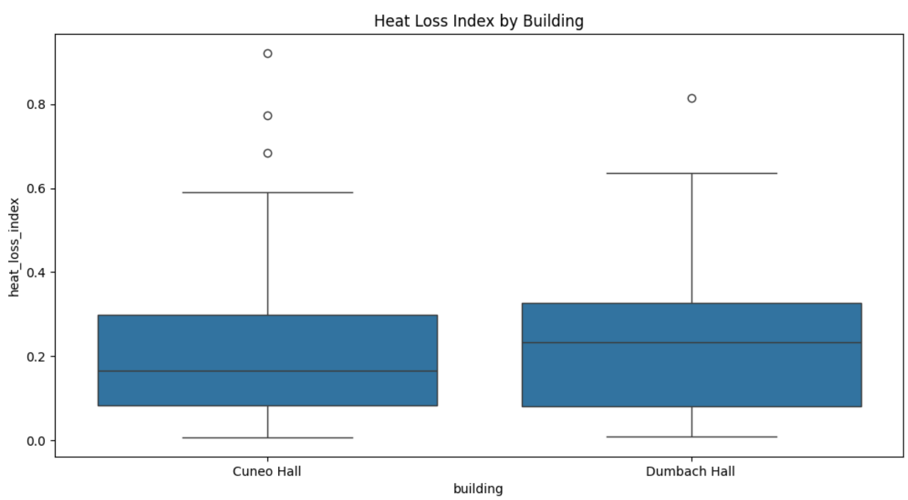
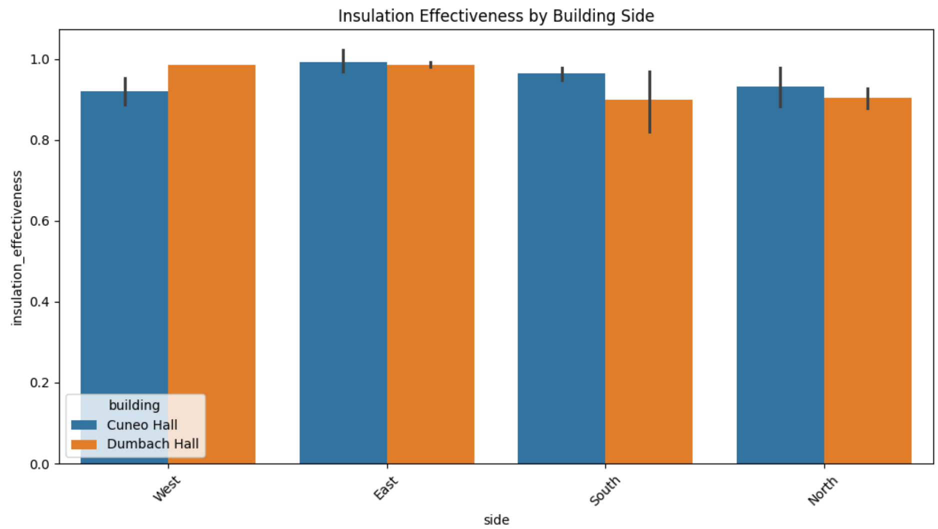


Directional Analysis

Perhaps the most revealing insights came from examining performance by building orientation. East-facing sections of both buildings showed exemplary performance, maintaining high insulation effectiveness. However, significant variations emerged in other orientations.

The south-facing sections of Dumbach Hall exhibited the highest heat loss (HLI: 0.36), while Cuneo Hall maintained more consistent performance across all orientations. North-facing sections of both buildings showed moderate heat loss, likely due to reduced solar gain and exposure to prevailing winds.

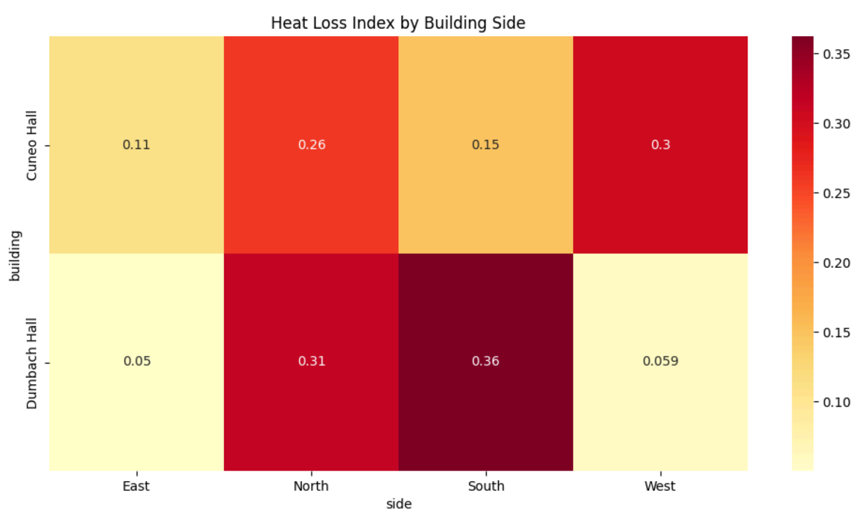


Critical Areas

The analysis identified several areas requiring attention:

In Cuneo Hall, the most significant heat loss was observed on the west side, with a temperature differential of -4.36°F (HLI: 0.92). Two additional areas on the west face showed differentials of -3.03°F and -2.30°F respectively.

Dumbach Hall's most critical area was its south entrance, showing a temperature differential of -7.78°F (HLI: 0.81). The north entrance (-2.41°F, HLI: 0.64) and another south section (1.53°F, HLI: 0.62) also showed concerning heat loss patterns.



Discussion

The results demonstrate that while both buildings maintain generally acceptable thermal performance, specific areas require targeted improvements. The more consistent performance of Cuneo Hall suggests benefits from its construction methods or more recent maintenance. Dumbach Hall's greater variability, particularly in its south-facing sections, indicates potential opportunities for energy efficiency improvements.

The disparity in performance between different building orientations highlights the importance of considering directional factors in building maintenance and renovation planning. The superior performance of east-facing sections provides a benchmark for potential improvements to other orientations.

Conclusion

This study highlights the potential of thermal imaging and data science to address critical challenges in building energy efficiency and sustainability. By focusing on the windows of Dumbach Hall and Cuneo Hall at Loyola University Chicago's Lakeshore Campus, the project combined advanced technologies and analytical methods to identify heat anomalies, assess insulation quality, and provide actionable insights.

The integration of thermal imaging, data logging, and statistical analysis revealed significant findings. Heat leakage was most pronounced in poorly framed windows and south-facing sides, underscoring the importance of structural integrity and environmental orientation in energy management. Image processing techniques, such as contour detection and histogram equalization, enhanced the visibility of thermal patterns, enabling precise identification of problem areas. The exploratory use of machine learning models further demonstrated the potential for automating anomaly detection, paving the way for more scalable solutions. Through the development of the *Loyola Thermal Image Registry* and a Power BI dashboard, the project showcased innovative approaches to data management and visualization. These tools not only streamlined the analysis process but also provided an interactive platform for stakeholders to explore findings and make informed decisions.

The implications of this research extend beyond the immediate scope of the campus. The methodologies and insights presented here offer a replicable framework for evaluating energy efficiency in other buildings and environments. By addressing heat leakage and optimizing insulation, institutions can achieve significant energy savings, reduce environmental impact, and enhance the longevity of their infrastructure. Future directions for this work include expanding the dataset to cover additional buildings and seasonal variations, incorporating IoT-enabled devices for real-time data collection, and refining machine learning models to improve accuracy.

These advancements will further elevate the impact of this research, supporting broader sustainability initiatives and advancing the field of thermal analysis.

In conclusion, this project demonstrates how data science and thermal imaging can transform traditional energy audits into more precise, actionable, and scalable processes. It serves as a testament to the power of interdisciplinary approaches in solving complex, real-world problems and lays the groundwork for future innovations in sustainable infrastructure management. Through this study, Loyola University Chicago takes an important step toward a more energy-efficient and environmentally conscious future.