A REPORT
ON

Non-Contact Estimation of Thermal Properties of Engineering Structures

Submitted by,

Mr. Avyukth Potnuru - 20211CAI0123

Under the guidance of,

Mr. Likhith S R

in partial fulfillment for the award of the degree of

BACHELOR OF TECHNOLOGY

IN

COMPUTER SCIENCE AND ENGINEERING

At

GAIN MORE KNOWLEDGE
REACH GREATER HEIGHTS

PRESIDENCY UNIVERSITY

BENGALURU

MAY 2025

PRESIDENCY UNIVERSITY

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CERTIFICATE

This is to certify that the Internship/Project report **"Non-Contact Estimation of Thermal Properties of Engineering Structures"** being submitted by Avyukth Potnuru bearing roll number "20211CAI0123" in partial fulfillment of the requirement for the award of the degree of Bachelor of Technology in Computer Science and Engineering is a bonafide work carried out under my supervision.

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DECLARATION

I hereby declare that the work, which is being presented in the report entitled **"Non-Contact Estimation of Thermal Properties of Engineering Structures"** in partial fulfillment for the award of Degree of **Bachelor of Technology** in **Computer Science and Engineering (AI & ML)**, is a record of my own investigations carried under the guidance of **Mr. Likhith S R, Assistant Professor, Presidency School of Computer Science and Engineering, Presidency University, Bengaluru.**

I have not submitted the matter presented in this report anywhere for the award of any other Degree.

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To Whom It May Concern

This is to certify that Avyukth Potnuru (enrolled in a B. Tech program in Computer Science and Engineering (AI & ML) at Presidency University) has completed his internship in my lab at Mechanical Engineering, Indian Institute of Technology Kanpur, from 27/01/2025 to 05/05/2025. He explored the application of "Deep Learning for Non-Contact Estimation of Thermal Properties of Engineering Structures". He had (i) conducted a detailed literature survey on AI models and (ii) adopted, validated, and implemented various AI models. This internship exposed him to engineering applications of his coursework and provided him with first-hand experience in scientific research. His performance in this internship has been good, with an equivalent rating of over 9/10.

Thank you,

C. Chandraprakash
Associate Professor

ABSTRACT

This project proposes a novel deep learning-based framework for the non-contact estimation of thermal properties namely thermal conductivity, density, and specific heat capacity of engineering structures. Traditional methods often require physical contact or destructive testing, which limits real-time and safe evaluations. In contrast, this approach leverages pulsed thermography and infrared (IR) image sequences to infer thermal diffusivity through a 3D Convolutional Neural Network (3D CNN). Synthetic and simulated data are generated via COMSOL Multiphysics simulations and controlled thermographic imaging, then preprocessed for model training. The model learns spatio-temporal heat diffusion patterns to accurately predict thermal characteristics. This contactless technique offers a scalable, cost-effective, and reliable alternative suitable for structural health monitoring, especially in inaccessible or sensitive environments, while preserving material integrity.

ACKNOWLEDGEMENTS

First of all, we indebted to the **GOD ALMIGHTY** for giving me an opportunity to excel in our efforts to complete this project on time.

We express our sincere thanks to our respected dean **Dr. Md. Sameeruddin Khan**, Pro-VC - Engineering and Dean, Presidency School of Computer Science and Engineering & Presidency School of Information Science, Presidency University for getting us permission to undergo the project.

We express our heartfelt gratitude to our beloved Associate Dean **Dr. Mydhili K Nair,** Presidency School of Computer Science and Engineering, Presidency University, and Dr. Zafar Ali Khan N, Head of the Department, Presidency School of Computer Science and Engineering, Presidency University, for rendering timely help in completing this project successfully.

We are greatly indebted to our guide **Mr. Likhith S R, Assistant Professor** and Reviewer **Mr. Santhosh Kumar K L, Assistant Professor**, Presidency School of Computer Science and Engineering, Presidency University for his inspirational guidance, and valuable suggestions and for providing us a chance to express our technical capabilities in every respect for the completion of the internship work.

We would like to convey our gratitude and heartfelt thanks to the CSE7301 Internship/University Project Coordinator **Mr. Md Ziaur Rahman and Dr. Sampath A K,** department Project Coordinators **Dr. Afroz Pasha, Assistant Professor** and Git hub coordinator **Mr. Muthuraj.**

We thank our family and friends for the strong support and inspiration they have provided us in bringing out this project.

Avyukth Potnuru

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Chapter 1

INTRODUCTION

The evaluation of thermal properties such as thermal conductivity (k), density (ρ), and specific heat capacity (Cp) is fundamental to understanding the structural and thermal performance of engineering materials. These properties influence how materials behave under thermal stress, how heat is distributed and dissipated, and how materials degrade over time. Accurate estimation of these thermal characteristics is essential in fields such as aerospace, civil engineering, electronics, manufacturing, and energy systems, where maintaining structural integrity under varying thermal conditions is critical.

Traditional methods for measuring these thermal properties typically involve direct contact techniques such as laser flash analysis, guarded hot plate, or differential scanning calorimetry or even destructive testing. While effective, these approaches have several drawbacks: they are often invasive, time-consuming, costly, and not suitable for in-situ or real-time applications. These limitations are particularly problematic for sensitive, hazardous, or complex structures, such as those found in nuclear facilities, aerospace components, or heritage artifacts, where physical contact is either impractical or risks damaging the material.

With the growing availability of infrared (IR) thermographic imaging and computational modeling, non-contact approaches have emerged as promising alternatives. IR thermography enables the visualization of surface temperature evolution over time by capturing thermal radiation. When combined with machine learning or deep learning algorithms, these sequences of thermal images can be analyzed to extract meaningful patterns that correspond to internal material properties.

This project focuses on the non-contact estimation of thermal properties using time-series IR thermographic data processed through deep learning models. Specifically, a 3D Convolutional Neural Network (3D CNN) is developed to capture spatio-temporal patterns in heat diffusion observed across image frames. By learning from both simulated and experimental IR datasets, the model is trained to predict thermal diffusivity a key intermediate metric along with core thermal parameters such as thermal conductivity, density, and specific heat capacity.

Synthetic thermal image sequences are generated using COMSOL Multiphysics, a simulation platform based on the Finite Element Method (FEM), to simulate controlled heat transfer scenarios in various materials. These are augmented with experimentally collected IR data, ensuring that the model is exposed to both idealized and realistic conditions. This dual-source approach improves the robustness, generalizability, and practical relevance of the resulting system.

The ultimate goal of the project is to design a scalable, accurate, and non-invasive solution for thermal property estimation that can be applied across diverse materials and industrial settings. Such a system could greatly benefit applications in structural health monitoring, failure prediction, material science research, and automated inspection systems, significantly reducing the dependence on traditional testing setups and human intervention.

Chapter 2

LITERATURE SURVEY

As per [1], Gated Recurrent Units (GRUs) have been used for defect depth estimation in Carbon Fiber Reinforced Polymer (CFRP) using pulsed thermography. The study employed simulated infrared thermography data generated using the Finite Element Method (FEM). The preprocessing involved normalization and structuring of time-series data for training. The model achieved an accuracy of 90% with raw data, which improved to over 95% after normalization. However, since the model was trained on simulated data, it faces challenges in generalizing to real-world applications.

Study [2] integrates Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) for defect detection and depth estimation used various architectures such as ConvLSTM2D and VGG-UNet. Yolo-v3 performed exceptionally well in spatial defect detection with training accuracies above 99%, while GRU models achieved 95% accuracy in defect depth estimation after data normalization. Hybrid models such as ConvLSTM2D effectively reconstructed defect structures, though they struggled with edge details. The study highlighted the advantage of spatial-temporal models in defect characterization.

A CNN-based model was developed for simultaneous prediction of multiple soil properties using visible-near-infrared (vis-NIR) and mid-infrared (MIR) spectral data. The CNN outperformed traditional regression models like Partial Least Squares Regression (PLSR) and Cubist models, achieving an R^2 value of 0.98 for MIR data. The study [3] used the Kellogg Soil Survey Laboratory (KSSL) database, which provided spectral and reference soil property measurements. Although the CNN approach proved superior, it required a large dataset and significant computational resources.

In [4] CNNs were also used to predict the creep properties of high-temperature exposed CMSX-4 nickel-based superalloy. The study incorporated two-point spatial correlation analysis to improve model accuracy by linking microstructural features to mechanical properties. The model achieved high accuracy with an R^2 value of 0.98 for creep life prediction. However, the study focused solely on CMSX-4, limiting its general applicability to other alloys.

An optimized 2D CNN based on a modified AlexNet architecture was used to predict the effective thermal conductivity of composite materials in [5]. The study found that parallel cross-section inputs improved accuracy by 35% compared to perpendicular cross-sections. The CNN achieved performance levels comparable to 3D CNNs while significantly reducing computational time. However, obtaining high-quality 3D structure data remains a challenge.

Study [6] leverages U-Net and MobileNet for brain tumor classification combined CNN-based image analysis with a voting classifier using logistic regression and stochastic gradient descent. The U-Net model achieved 99.64% accuracy, while MobileNet reached 97.28%. The approach effectively integrated image and numerical data for classification, though data augmentation introduced potential noise.

A Mask R-CNN model incorporating ResNet101-FPN was developed for detecting surface and subsurface defects in heritage artifacts using thermal imaging by the authors of study [7]. The model achieved a mean precision of 99.28% and successfully segmented defect regions. Two novel pre-processing algorithms improved contrast between defective and intact areas. However, environmental factors and heating/cooling uniformity influenced performance.

Linear regression and CNN-based models were applied in study [8] to infer thermodynamic properties and directional processes in spin chains. The study found that linear regression worked well for simple systems, while CNNs were better suited for complex relationships. However, model accuracy decreased for highly irreversible processes, and overlap in trajectory data reduced prediction precision.

A machine learning approach using LSTM networks was employed to predict lattice thermal conductivity based on fundamental material properties in study [9]. The study used a dataset of 350 experimentally measured samples. LSTM outperformed other models, achieving an RMSE of 8.36 and an R^2 of 0.88. Despite strong results, the limited dataset size posed a challenge for supervised learning.

In this study [10] of Defect characterization in additive materials was explored using multiple machine learning models, including linear regression, Gaussian process regression (GPR), and support vector machines (SVM). GPR with a rational quadratic kernel performed best in predicting defect length ($R^2 = 0.92$), while interaction regression excelled in thickness prediction ($R^2 = 0.79$). Thermal contrasts were key predictive features, but models like SVM and MLP showed reduced accuracy for small datasets.

A Restricted Boltzmann Machine (RBM) was used to analyze phase transitions in Ising models. The model identified critical points and regions of high specific heat with near-theoretical accuracy. However, the study [11] found that excessive hidden neurons led to overlearning and noise-dominated configurations.

In study [12], an adversarial autoencoder (AAE) and a structure-preserving neural network (SPNN) were employed for thermodynamics-informed super-resolution of scarce temporal dynamics data. The approach significantly improved resolution while maintaining thermodynamic constraints. The method achieved a mean relative error of less than 3% and was 37× faster than traditional bicubic interpolation for Newtonian cases. However, the study relied on synthetic data and lacked real-world validation.

Chapter 3

RESEARCH GAPS OF EXISTING METHODS

Although significant progress has been made in applying machine learning and deep learning techniques, several critical challenges and limitations persist. Based on the literature reviewed, the following research gaps have been identified:

3.1 Generalization Limitations

Many models demonstrate high performance on simulated datasets but fail to generalize effectively to real-world scenarios:

- Models trained exclusively on simulated infrared thermography data (e.g., via FEM) [1] perform well under controlled conditions but lack robustness when exposed to real-world noise and environmental variability.

- Adversarial Autoencoders (AAEs) and similar super-resolution techniques [12] offer speed and accuracy, yet they too often rely on synthetic input and lack validation against actual measurement data.

3.2 Limitations in Spatiotemporal Modeling

- Hybrid models like ConvLSTM2D and VGG-UNet [2] are adept at learning spatial-temporal patterns but struggle with fine detail reconstruction, especially around defect boundaries, which is critical for precise thermal property estimation.

- Edge detail degradation in defect maps significantly affects the interpretability and reliability of predictions for structural diagnostics.

3.3 Data and Computational Requirements

- Several approaches, such as CNN-based soil property prediction [3] and creep life estimation in alloys [4], require large annotated datasets and high-performance computing resources, limiting their scalability for real-time or in-field use.

- The need for expensive and high-quality 3D structure data [5] presents a significant bottleneck in extending these models to practical applications.

3.4 Material-Specific Model Constraints

- Models such as those trained on CMSX-4 alloys [4] or other specific materials exhibit high accuracy but lack generalizability across a wide range of materials and structural configurations.

- This narrow applicability limits their use in industrial or heterogeneous material environments, where models must perform well across varied substrates.

3.5 Environmental and Measurement Variability

- Approaches using thermal imaging for heritage artifacts [7] or brain tumor classification [6] demonstrate sensitivity to external environmental factors, such as lighting, temperature drift, and heating uniformity, which reduces model reliability in uncontrolled settings.

- This calls for robust models capable of compensating for or adapting to environmental noise.

3.6 Inadequacy of Small or Imbalanced Datasets

- Studies using limited sample sizes (e.g., 350 samples for LSTM-based thermal conductivity prediction [9]) highlight how small datasets hinder model accuracy and increase overfitting risks.

- Traditional supervised learning is insufficient under such constraints, emphasizing the need for semi-supervised, transfer learning, or self-supervised learning strategies.

3.7 Real-Time Application Challenges

- While high-performing models exist, few are designed or optimized for real-time processing of thermal data streams, especially in operational or in-situ monitoring environments.

- Latency, hardware compatibility, and processing overhead need to be addressed for deployment in industrial monitoring systems.

3.8 Need for Multi-Modal Fusion Techniques

- Several works [2][6][8] attempt integration of different data modalities (e.g., thermal images, numerical signals), yet there remains a lack of unified frameworks combining spatial features (via CNNs) and temporal dependencies (via RNNs or Transformers).

- Developing end-to-end multi-modal models that can efficiently learn from both image sequences and sensor data could improve prediction robustness.

3.9 Bridging Synthetic–Real Domain Gap

- As seen in [1], [12], many studies demonstrate success with synthetic datasets but fail to address the domain shift between simulated and experimental conditions.

- There is a critical need for domain adaptation methods (e.g., adversarial domain adaptation, feature alignment techniques) that allow models trained on simulated data to perform reliably on real-world datasets.

3.10 Lack of Explainability and Interpretability

- Most deep learning models in the literature lack interpretability tools to explain predictions, making it difficult for domain experts to trust or validate results in high-stakes engineering contexts.

- Integration of explainable AI (XAI) techniques (e.g., SHAP, Grad-CAM) is needed to improve trust and support decision-making in deployment scenarios.

Chapter 4

PROPOSED METHODOLOGY

The proposed methodology is designed to estimate the thermal properties of engineering structures, namely thermal conductivity (k), density (ρ), and specific heat capacity (Cp), through a fully non-contact and image-based approach. By combining physics-based simulation, infrared (IR) image capture, and deep learning, this workflow ensures both accuracy and practical applicability. The entire pipeline is structured into several key stages: data acquisition, preprocessing, feature extraction, model architecture design, and model training and optimization.

4.1 Data Acquisition

To develop a robust model capable of learning spatio-temporal heat diffusion patterns, two types of IR datasets are collected:

- **Simulated Data**:

  Finite Element Method (FEM)-based simulations are performed using COMSOL Multiphysics to model transient heat transfer scenarios across different material configurations. These simulations generate synthetic IR time-series data, which provide well-controlled and annotated training examples. Varying boundary conditions, material properties, and initial temperature gradients are introduced to diversify the dataset.

- **Experimental Data**:

  Complementing the simulated data, experimental IR sequences are acquired using a thermal imaging camera in a controlled laboratory setting. Surface temperatures of test samples subjected to heating or cooling are recorded over time. This dataset helps bridge the gap between simulation and real-world data, enabling better generalization.

4.2 Data Preprocessing

Before feeding the data into the model, preprocessing is applied to standardize and structure the input format:

- **Normalization**:

  Pixel intensities from the IR sequences are normalized to a common range (e.g., 0 to 1 or Z-score normalization) to ensure consistent brightness and contrast levels across different sequences.

- **Resizing**:

  All IR frames are resized to a fixed spatial resolution (e.g., 64×64 or 128×128 pixels) to ensure compatibility with the input dimensions of the neural network.

- **Temporal Structuring**:

  Sequences are organized chronologically to preserve the thermal evolution over time. Each sample consists of a fixed number of frames (e.g., 20–50) representing a short thermal transient.

4.3 Feature Extraction

The critical information for predicting thermal properties lies in how heat diffuses across a material over time. To extract this:

- **Spatio-Temporal Encoding**:

  The IR sequences are treated as video volumes. By processing these sequences using 3D convolutional layers, both spatial (frame-wise heat distribution) and temporal (rate of change over time) features are extracted simultaneously.

- **Heat Flow Dynamics**:

  The learned features capture patterns such as heat concentration, spread velocity, and cooling rates, which are strongly correlated with the underlying thermal properties.

4.4 Model Architecture

A **3D Convolutional Neural Network (3D CNN)** is proposed due to its ability to effectively process volumetric data:

- **Input Layer**:

  Accepts tensors of shape *($T \times H \times W \times 1$)*, where T is the number of time steps (frames), H and W are frame height and width, and 1 denotes the grayscale IR channel.

- **Convolutional Layers**:

  Multiple 3D convolution layers (e.g., kernel size 3×3×3) are applied to learn local patterns across both spatial and temporal dimensions.

- **Activation Functions**:

  ReLU (Rectified Linear Unit) activations are used to introduce non-linearity after each convolutional block.

- **Pooling Layers**:

  3D MaxPooling layers reduce dimensionality and computational load while retaining important features.

- **Fully Connected Layers**:

  After flattening the feature map, dense layers interpret the learned spatio-temporal features and map them to the target physical properties.

- **Output Layer**:
  A regression output layer with three neurons provides continuous estimates of:

  - Thermal Conductivity (k)
  - Density (ρ)
  - Specific Heat Capacity (Cp)

4.5 Training and Optimization

The model is trained using supervised learning on labeled data (with known thermal properties):

- **Loss Function**:

The **Mean Squared Error (MSE)** is used as the loss function to quantify the deviation between predicted and ground-truth values.

- **Optimizer**:

  The **Adam optimizer** is selected due to its adaptive learning rate mechanism, which accelerates convergence and prevents overshooting.

- **Learning Rate Tuning**:

  A scheduler or learning rate decay strategy is employed to fine-tune the training process, ensuring convergence while avoiding local minima.

- **Validation Strategy**:

  A portion of the dataset is reserved for validation to monitor overfitting and generalization. Early stopping and dropout layers are introduced to enhance robustness.

Chapter 5

OBJECTIVES

The primary objective of this project is to develop a robust, non-contact framework for estimating the thermal properties of engineering materials using infrared thermography and deep learning. This approach aims to eliminate the need for invasive or destructive testing while maintaining high precision and adaptability across material types. The specific objectives are outlined below:

5.1. Develop a Non-Contact Estimation Framework

- Establish a reliable method for estimating key thermal properties which are thermal conductivity (k), density (ρ), and specific heat capacity (Cp) without requiring any physical contact with the specimen.
- Leverage the capabilities of thermal imaging to remotely capture temperature evolution on material surfaces during controlled thermal events.

5.2. Utilize Spatio-Temporal Temperature Distributions

- Exploit the dynamic patterns in temperature variation over time, as captured in IR image sequences, to infer the underlying thermophysical behavior of materials.
- Convert these sequences into time-series data that reflect heat flow, diffusion rates, and thermal inertia.

5.3. Integrate Deep Learning for Property Prediction

- Apply advanced deep learning techniques, particularly 3D Convolutional Neural Networks (3D CNNs), to extract meaningful spatio-temporal features and map them to material properties.
- Train models on both synthetic (simulated) and experimental datasets to ensure robustness and generalization.

5.4. Improve Accuracy, Efficiency, and Generalizability

- Enhance the precision of thermal property estimation by minimizing prediction error through optimized model architectures and preprocessing strategies.

- Enable rapid, automated analysis suitable for real-time or near-real-time applications.
- Ensure the framework can generalize across various engineering materials, structures, and environmental conditions.

5.5. Replace Conventional Testing with Scalable Alternatives

- Provide a viable alternative to traditional thermal characterization methods that are often destructive, time-consuming, or limited in scope.
- Maintain or exceed the reliability and repeatability of contact-based or laboratory methods while offering greater flexibility in deployment, including in-field or operational settings.

Chapter 6

SYSTEM DESIGN & IMPLEMENTATION

The proposed system is designed to estimate thermal properties, namely thermal conductivity (k), density (ρ), and specific heat capacity (Cp) using a non-contact, image-based approach. The entire workflow spans data generation, preprocessing, feature engineering, deep learning model development, and prediction.

6.1 System Overview

The system utilizes thermal image sequences (IR videos or frames) as input and outputs numerical values corresponding to the thermal properties of the material. It leverages both synthetic and experimental data, enabling training and validation of a deep learning model that generalizes across different conditions.

6.2 Data Collection and Simulation

- **Simulated Data Generation**
  Using COMSOL Multiphysics, heat transfer simulations are conducted based on the Finite Element Method (FEM). These simulations model heat diffusion through different material structures under various boundary conditions.
  - Simulated materials include metals, polymers, and composites.
  - Simulation parameters such as initial temperature, heating profiles, and geometric configurations are varied to build a diverse dataset.
- **Experimental Data Acquisition**
  Real infrared (IR) sequences are recorded using a thermal camera in a controlled laboratory setup. These sequences reflect how real materials respond to heating and cooling cycles and provide validation for the simulated data.

6.3 Data Preprocessing

To ensure consistency and quality of model inputs, the following preprocessing steps are applied:

- **Normalization**: All frames are normalized to a common intensity range to reduce variance due to ambient lighting or sensor sensitivity.
- **Resizing**: IR frames are resized to a fixed resolution to maintain uniform input

dimensions across the dataset.

- **Sequence Structuring**: Image sequences are organized as 3D arrays (time × height × width), preserving the temporal evolution of thermal patterns for deep learning models.

6.4 Feature Extraction

- Spatio-temporal features are extracted directly from the image sequences using convolutional operations within the 3D CNN.
- These features encapsulate:
    - **Spatial gradients**: Representing temperature variation across the material surface.
    - **Temporal dynamics**: Capturing how heat propagates through the material over time.

6.5 Model Development

A **3D Convolutional Neural Network (3D CNN)** is implemented to learn the mapping from IR image sequences to thermal properties.

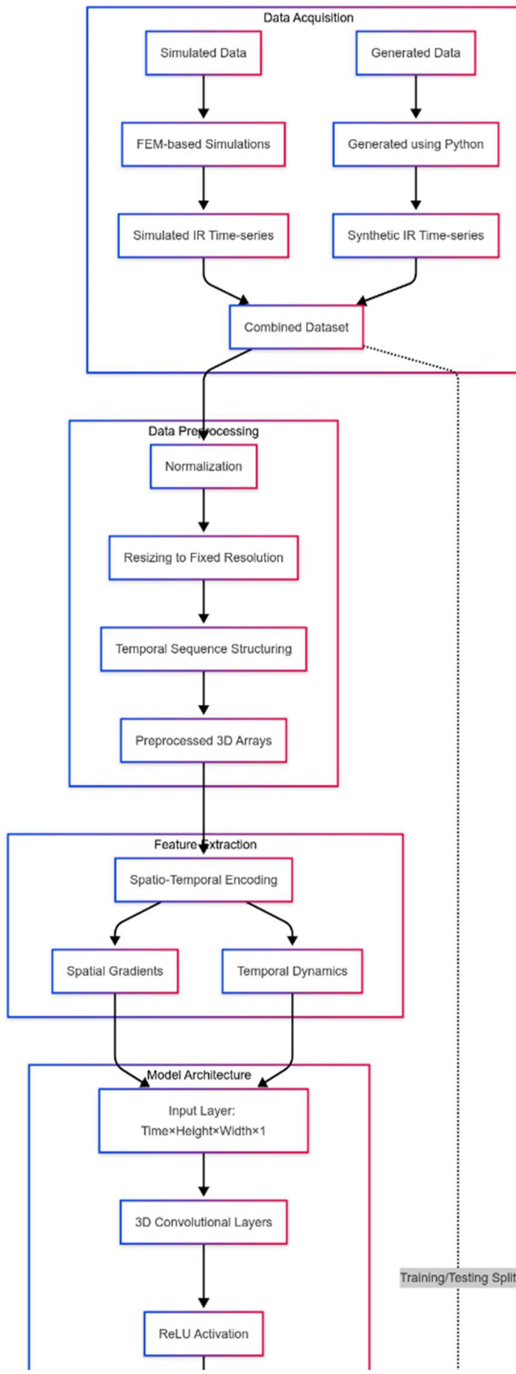
Model Architecture

- **Input Layer**: Accepts image sequences in the format (frames × height × width × channels).
- **3D Convolutional Layers**: Extracts spatial and temporal features using sliding 3D kernels.
- **Activation Functions**: ReLU is used to introduce non-linearity.
- **Pooling Layers**: 3D max pooling is applied to reduce feature dimensionality and control overfitting.
- **Fully Connected Layers**: Interprets the extracted features to perform regression.
- **Output Layer**: Produces three continuous values corresponding to:
    - Thermal Conductivity (k)
    - Density (ρ)
    - Specific Heat Capacity (Cp)

6.6 Training and Optimization

- **Loss Function**: Mean Squared Error (MSE) is used to quantify prediction error during training.

- **Optimizer**: The Adam optimizer is employed with a learning rate scheduler for stable convergence.
- **Batch Size and Epochs**: Tuned empirically to balance model performance and computational cost.
- **Validation**: Both simulated and experimental data are used for cross-validation to assess the model's generalization capabilities.



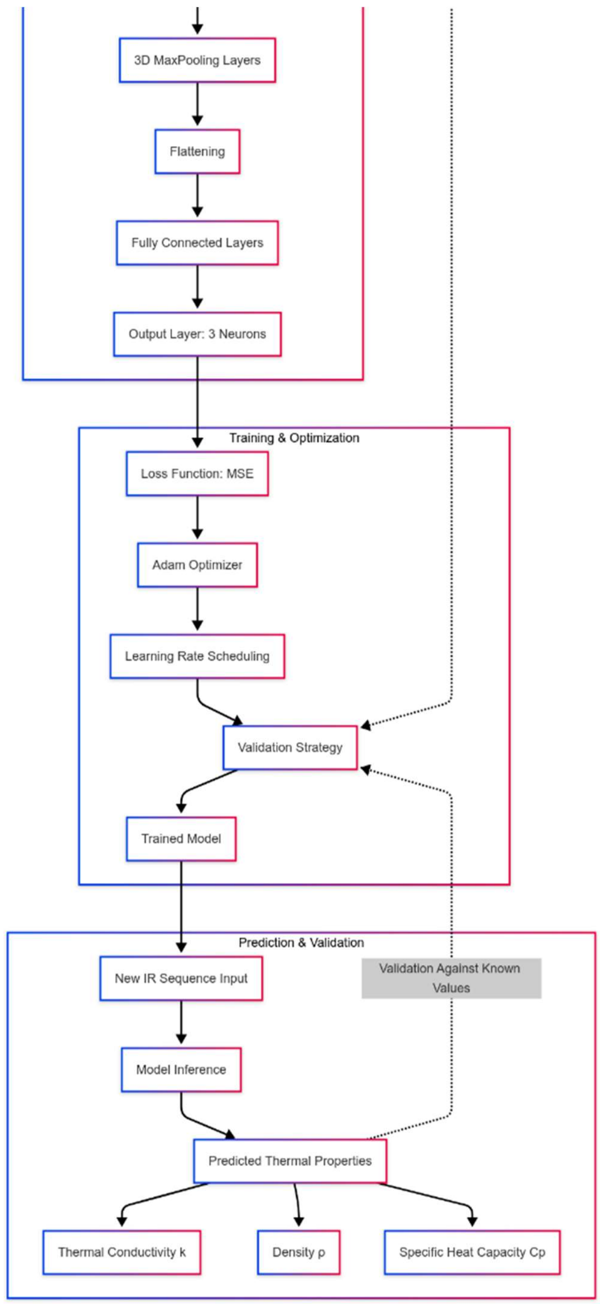


Figure 6. 1: System Design Diagram

As we can see from Figure 6.1, the thermal properties estimation system follows a sequential workflow from data acquisition through prediction, integrating both simulated and experimental thermal imaging data. The system processes these inputs through preprocessing and feature extraction stages before feeding them into a 3D CNN architecture, which ultimately outputs the three target thermal properties (conductivity, density, and specific heat capacity) while incorporating validation feedback to ensure model accuracy.

Chapter-7

TIMELINE FOR EXECUTION OF PROJECT
(GANTT CHART)

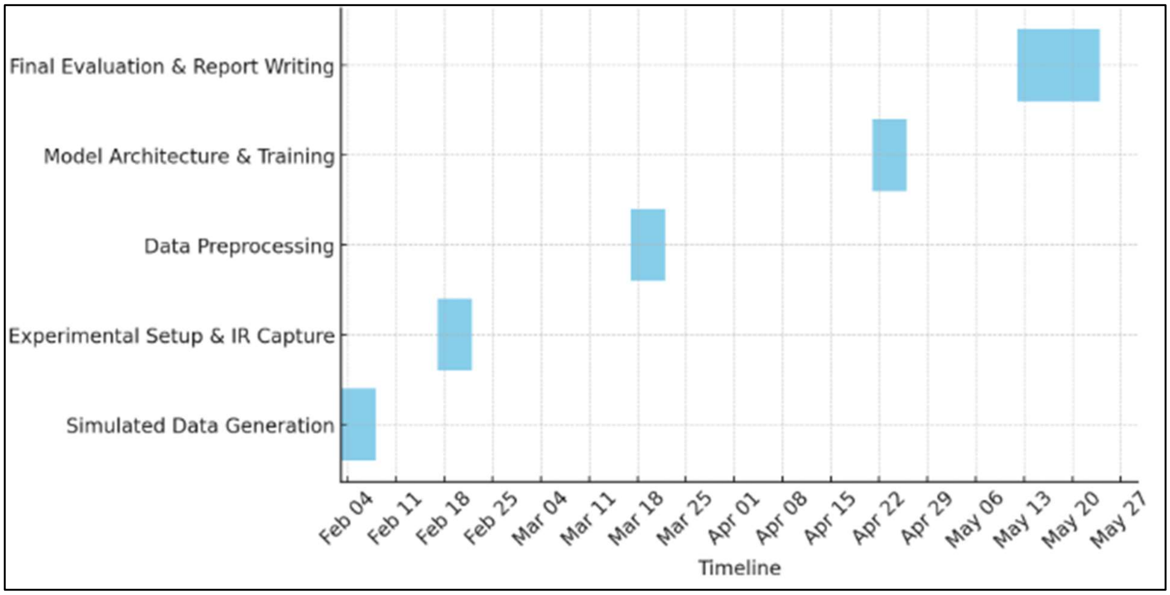


Figure 7. 1: Gantt Chart to display and inform project timeline and tasks

We can see in Figure 7.1 that the Gantt chart outlines the internship project timeline across five key review phases, beginning in early February 2025 and concluding with the final viva-voce in Mid-May 2025. Each review stage is aligned with specific tasks, enabling structured progress tracking from initial framework design and simulation setup to data collection, model development, and reporting. This visual representation helps in understanding the sequential flow and overlapping of activities, ensuring timely completion of milestones and preparation for evaluations.

Chapter 8

OUTCOMES

As the internship is currently in progress, the final results, particularly those involving quantitative evaluation and performance metrics are still under development. However, several critical milestones and intermediate outcomes have already been achieved, laying a strong foundation for the successful realization of the project objectives. These outcomes span across simulation design, experimental preparation, and deep learning implementation, and reflect meaningful progress toward the goal of contactless thermal property estimation.

8.1 Intermediate Outcomes

- **Framework Design and Integration**
  A comprehensive methodological pipeline has been conceptualized, detailing each stage from data acquisition to predictive modeling. This pipeline integrates computational simulation, infrared image preprocessing, and deep learning-based regression, creating a cohesive system for thermal analysis. The modular design allows for easy extension and real-world adaptability.
- **Synthetic Data Generation**
  High-resolution thermal datasets have been successfully generated using COMSOL Multiphysics simulations based on the Finite Element Method (FEM). These simulations model heat transfer through engineering materials under various boundary and initial conditions, producing infrared image sequences that reflect realistic thermal diffusion behavior. This synthetic dataset forms a crucial base for early-stage model development and testing.
- **Experimental Setup Development**
  An initial experimental environment has been established to capture real IR thermal image sequences under controlled heating and cooling conditions. These real-world measurements are designed to supplement the synthetic data and ensure that the model is exposed to the types of variability encountered in practical applications, such as sensor noise, material heterogeneity, and ambient interference.
- **3D CNN Model Architecture Design**
  A custom 3D Convolutional Neural Network (3D CNN) architecture has been developed to learn from spatio-temporal patterns in the IR sequences. The model is

designed to map image time series to underlying thermal properties, effectively capturing both spatial features (heat spread patterns) and temporal evolution (rate of temperature change). The architecture includes convolutional, pooling, and fully connected layers optimized for regression tasks.

- **Preprocessing and Implementation Progress**
  Core preprocessing operations such as image normalization, dimensional resizing, and time-series structuring have been implemented to standardize the data for deep learning input. These preprocessing steps ensure consistency across different datasets and improve the quality of feature extraction during model training.
- **Model Training and Optimization (Ongoing)**
  Training and fine-tuning of the deep learning model are currently underway. Optimization techniques, including learning rate scheduling, early stopping, and data augmentation, are being applied to improve generalization and convergence stability.

8.2 Anticipated Outcomes

Based on the current progress and the strength of the underlying framework, the following key outcomes are anticipated upon project completion:

- **Non-Contact Estimation of Thermal Properties**
  A deep learning model capable of accurately predicting thermal conductivity (k), density (ρ), and specific heat capacity (Cp) without requiring physical contact or invasive procedures.
- **Scalable and Reliable Diagnostic Tool**
  A versatile system suitable for deployment in real-world industrial and research settings, providing rapid thermal diagnostics for a wide variety of engineering materials and structural components.
- **Cross-Domain Generalization**
  A model that demonstrates robust performance across both simulated and experimentally acquired datasets, ensuring its reliability in controlled lab environments as well as practical field applications.
- **Knowledge Contribution**
  The project is expected to contribute valuable insights into the integration of simulation-driven data and deep learning for material property inference, potentially informing future studies and industry practices in non-destructive testing, thermal

metrology, and smart manufacturing.

Chapter 9

RESULTS AND DISCUSSIONS

As this project is currently in progress, the final results of the deep learning model for thermal property estimation are not yet available. However, several key milestones have been achieved that lay the groundwork for upcoming evaluations:

- **Data Preparation:** Synthetic infrared (IR) datasets have been generated through COMSOL Multiphysics simulations, and experimental IR image sequences have been collected under controlled conditions. These datasets capture the thermal behavior of various engineering structures.
- **Model Architecture:** A custom 3D Convolutional Neural Network (3D CNN) has been designed to analyze the spatio-temporal characteristics of heat diffusion and output estimates for thermal conductivity (k), density (ρ), and specific heat capacity (Cp).
- **Ongoing Work:** The training and optimization of the model are underway. Preliminary assessments will focus on loss convergence, prediction consistency, and generalization from simulated to experimental data.
- **Expected Evaluations:**
    - **Quantitative Metrics:** Model performance will be evaluated using metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R^2 score.
    - **Comparative Analysis:** Results will be compared with traditional estimation techniques and prior machine learning approaches to assess relative accuracy and efficiency.
    - **Robustness Check:** Sensitivity to environmental conditions and data noise will be tested to understand model reliability in real-world scenarios.

The final outcomes will be documented and analyzed upon completion of the training and testing phases. These discussions will provide insights into the model's strengths, limitations, and scope for further improvement.

Chapter 10

CONCLUSION

This internship project sets the foundation for developing a non-contact, deep learning-based framework to estimate the thermal properties of engineering structures using infrared (IR) image sequences. The proposed methodology integrates simulation-based data generation, IR image preprocessing, and the design of a 3D Convolutional Neural Network (3D CNN) to model heat diffusion and predict material-specific thermal characteristics such as thermal conductivity, density, and specific heat capacity.

The initial phases includes literature review, identification of research gaps, methodology design, and partial implementation have been successfully completed. Simulated and experimental IR datasets have been prepared, and a custom 3D CNN architecture has been designed to handle the spatio-temporal dynamics of thermal patterns in the image sequences.

As the internship progresses, the focus will shift toward:

- Completing the training and validation of the deep learning model.
- Analyzing its performance on synthetic and experimental data.
- Fine-tuning the network to improve prediction accuracy and generalization.

Though final results are not yet available, the framework holds strong potential to serve as a non-invasive, data-driven alternative to conventional thermal property estimation methods. It offers promising applicability in industrial inspection, non-destructive testing, and material evaluation.

Further work will aim to refine the model, expand the dataset across material types and conditions, and evaluate real-time inference capabilities.

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APPENDIX-A

PSUEDOCODE

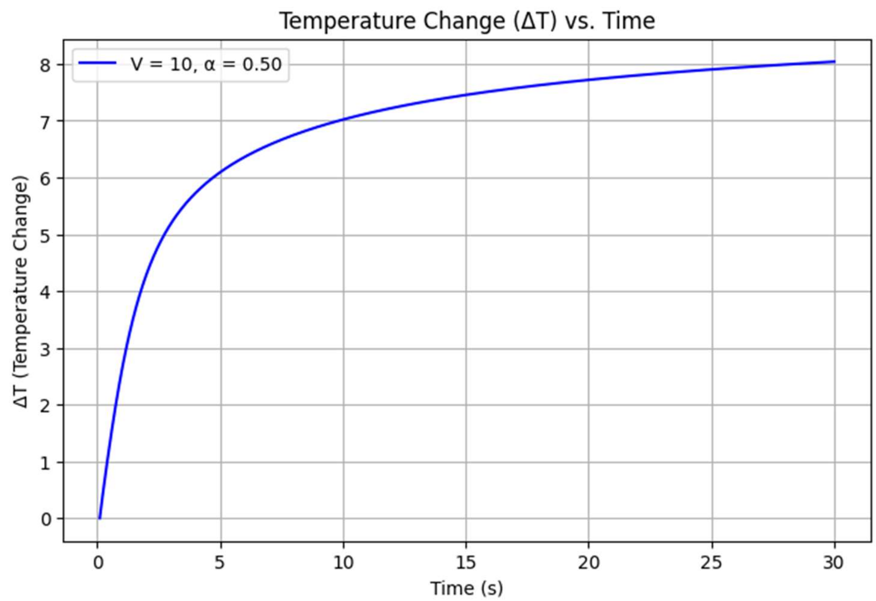
```
V_values = np.arange(1, 65)
alpha_values = np.linspace(0.5, 5, 10)
l, a, b = 1, 2, 1
N = 50
fps = 60
duration = 30
tot_frames = fps * duration
time_steps = np.round(np.linspace(0.1, duration, tot_frames), 2)

save_path = "/content/drive/MyDrive/Colab Notebooks/thermal_data_npy"
os.makedirs(save_path, exist_ok=True)

csv_file = os.path.join(save_path, "labels.csv")

def f(x):
    return (a * x) + b

def compute_integrals():
    n_vals = np.arange(N)
    coeffs = (2 * n_vals + 1) * np.pi / (2 * l)
    return np.array([quad(lambda x_dash: f(x_dash) * np.cos(c * x_dash), 0, l)[0] for c in
coeffs])

precomputed_integrals = compute_integrals()

def v(x, t, V, alpha):
    x = np.asarray(x)
    n_vals = np.arange(N)
    coeffs = (2 * n_vals + 1) * np.pi / (2 * l)
    exp_terms = np.exp(-alpha * (2 * n_vals + 1) ** 2 * np.pi ** 2 * t / (4 * l ** 2))[:, None]
```

```
    cos_terms = np.cos(np.outer(coeffs, x))
    term_sums = exp_terms * cos_terms * (
        (2 * l * (-1) ** (n_vals + 1) * V / ((2 * n_vals + 1) * np.pi))[:, None] +
precomputed_integrals[:, None]
    )
    return V + (2 / l) * np.sum(term_sums, axis=0)

def theta(x, y, t, V, alpha):
    t = np.maximum(t, 1e-6)
    return v(x, t, V, alpha) * erfc(np.abs(y) / (2 * np.sqrt(alpha * t)))

x_values = np.linspace(-l, l, 50)
y_values = np.linspace(-2 * l, 2 * l, 50)
X, Y = np.meshgrid(x_values, y_values)

with open(csv_file, "a", newline="") as f:
    writer = csv.writer(f)



    if os.stat(csv_file).st_size == 0:
        writer.writerow(["sequence_path", "alpha"])

    for V in V_values:
        for alpha in alpha_values:
            sequence_folder = os.path.join(save_path, f"Case_V_{V}_alpha_{alpha:.2f}")



            existing_files = [file for file in os.listdir(sequence_folder) if file.endswith(".npy")] if
os.path.exists(sequence_folder) else []
            if len(existing_files) == tot_frames:
                print(f"Skipping sequence: {sequence_folder}, already has {tot_frames} .npy
files.")
                continue
```

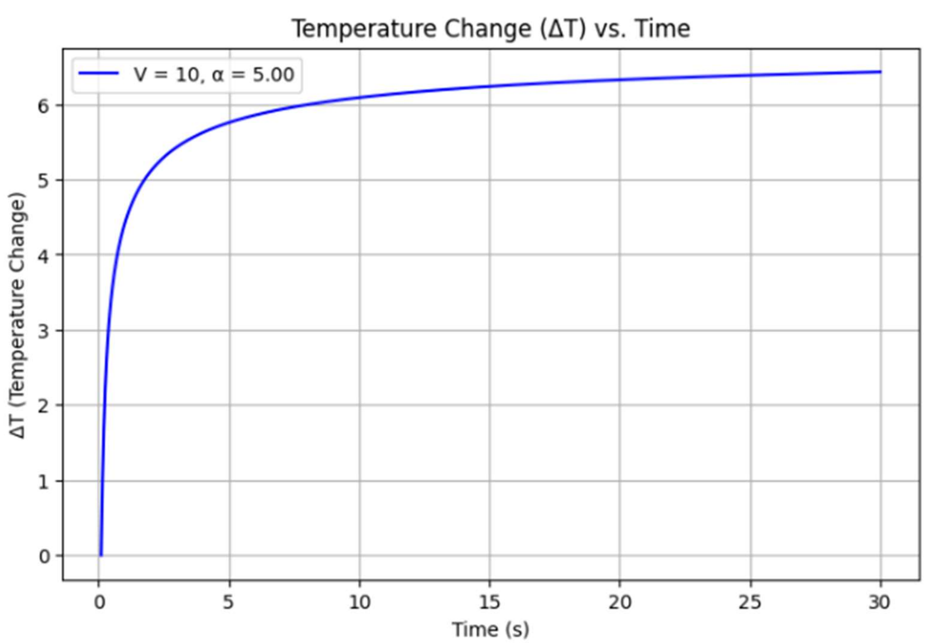
```
        os.makedirs(sequence_folder, exist_ok=True)

        for t in time_steps:
            theta_values = theta(X.flatten(), Y.flatten(), t, V, alpha).reshape(X.shape)

            # Save in .npy format
            filename = f"temp_t_{t:.2f}.npy"
            filepath = os.path.join(sequence_folder, filename)
            np.save(filepath, theta_values)


        writer.writerow([sequence_folder, alpha])
        f.flush()  # Ensure writing to disk

        print(f"Saved sequence: {sequence_folder}, Alpha: {alpha}")

print("Dataset and labels saved successfully!")
```

APPENDIX-B

SCREENSHOTS



Graph 1: Thermal Dispersion over Time(t) with α = 0.5



Graph 2: Thermal Dispersion over Time(t) with α = 5

The two graphs illustrate the relationship between temperature change (ΔT) and time under a constant heat input (V = 10), with varying values of thermal diffusivity (α). Both plots aim to show how the rate at which temperature changes over time is influenced by the material's ability to conduct and store heat.

In graph 1, where α = 0.50, the temperature change starts off steep but gradually increases over time, continuing to rise even after 30 seconds. This indicates that the material has low thermal diffusivity, meaning it slows the rate at which heat spreads throughout the material. As a result, heat accumulates over time, leading to a higher overall temperature change. The slower diffusion process causes the system to heat up more gradually but to a greater extent in the long run.

In graph 2 with α = 5.00, the temperature rises rapidly in the initial seconds and then quickly plateaus. This behavior reflects high thermal diffusivity, where the material conducts heat efficiently and reaches thermal equilibrium faster. Because the heat spreads quickly, there is less accumulation of energy in any specific region, resulting in a lower peak temperature change, but it is reached much sooner compared to the case with lower α.

Overall, these graphs clearly demonstrate how increasing the thermal diffusivity leads to faster temperature response but less sustained heating, while lower diffusivity results in slower heating but higher long-term temperature gain.

APPENDIX-C

ENCLOSURES

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SUSTAINABLE DEVELOPMENT GOALS

SDG 7 – Affordable and Clean Energy

By enabling precise thermal characterization of materials without physical contact, the project enhances the efficiency of thermal management systems in buildings, electronics, and industrial processes. This contributes to the development of energy-efficient technologies and supports the global transition to affordable and clean energy solutions.

SDG 9 – Industry, Innovation and Infrastructure

This project leverages advanced AI technologies (such as neural networks, and IR image analysis) and cloud-based platforms (like Google Colab) to develop non-contact, scalable solutions for estimating thermal properties of engineering materials. This directly supports innovation in material diagnostics and promotes resilient, intelligent infrastructure for industrial and scientific applications.

SDG 12 – Responsible Consumption and Production

This project supports sustainable engineering by optimizing material use based on data-driven insights into thermal behavior. Reducing the need for destructive testing and enabling predictive diagnostics minimizes material waste and promotes more sustainable production cycles.

SDG 13 – Climate Action

Accurate thermal modeling is crucial for designing climate-resilient infrastructure and energy systems. By improving our ability to assess and optimize thermal performance, this project contributes to adaptive solutions for climate change mitigation and efficient energy usage.