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Wood Chip Moisture Content Assessment Using Infrared Image-Based Machine Learning

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Introduction

- Wood chips are a critical biofuel source (pellets) and essential in the pulp & paper industry.
- Moisture content (MC) of wood chips affects the efficiency and quality of the final product.
- Traditional MC measurement methods are time-consuming and destructive.
- **Research Gap:** There is a need for a rapid, non-destructive, real-time MC assessment method to optimize industrial processes.



Fig 1. Wood Chips

Significance of Moisture Content Measurement

- Moisture content has an inverse relationship with the Net Calorific Value (NCV).
- Bio-fuel mills apply external heat to evaporate the extra water from the chips.
- Several production parameters depend on moisture content.

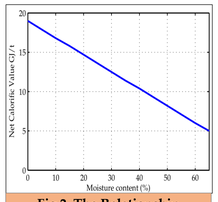


Fig 2. The Relationship Between MC & NCV

Challenges:

- Time-Consuming: Oven-drying takes hours.
- Destructive: Methods ruin samples.
- No Real-Time Data: Instant measurements unavailable.
- Labor-Intensive: Significant manual intervention needed.

Proposed Solution:

- Utilize infrared (IR) imaging to capture the temperature variations on the surface of wood chips, which correlate with their moisture content.
- Develop a machine learning model that can process these IR images to predict moisture content in real-time.

Problem Statement

Wood chip dataset (X_i, Y_i):	Thermal images and moisture content labels.
Moisture Content Classifier $f^*: X_i \rightarrow Y_i$:	Machine learning model to predict moisture content.
Predicted Moisture Class Y_i:	Output moisture class based on the model's prediction.

Literature Review

Method	Real-time Applicable	Interpretable	Non-destructive	Global Assessment	Time Consumption
Gravimetric	×	√	×	×	High
NIR Spectroscopy	√	√	√	×	Medium
Electrical Capacitance	×	×	√	×	Medium
Time Domain Reflectometry	√	×	√	×	Medium
Proposed (Ours)	√	√	√	√	Low

Our Contribution

1. Developed a novel, real-time machine learning (ML) method for **non-destructive moisture content (MC) estimation**, boosting efficiency and quality for biofuel and pulp industries.
2. Enhanced MC prediction by **preprocessing thermal images with ambient temperature and humidity data**.
3. Improved model accuracy using **Bayesian optimization to fine-tune** ML algorithms.

Proposed Method

Chip Sourcing & Preparing

- Collect wood chips from industrial pellet mill sites.
- Dry the chips in an oven at 105°C for 24 hours.
- Rehydrate chips by adding calculated amounts of water.
- Mix water evenly using a rotating mortar mixer.

Sample Image Collection

- Place wood chips in aluminum foil trays.
- Use a closed box with consistent lighting.
- Capture thermal images using a FLIR ONE Gen 3 camera.
- Take 20 images per tray, shuffling chips between shots.

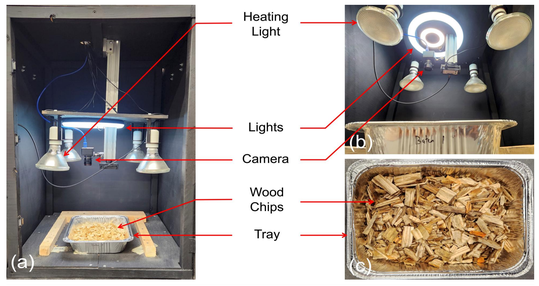


Fig 3. Setup for Data Collection

Preprocessing Thermal Image

- Extract temperature readings from thermal images.
- Adjust temperature readings based on ambient conditions.
- Exclude non-wood chip areas from images by cropping to the central 25% of the image.

Data Labeling

- Dry: ≤ 15%, Medium: 16 − 35%, Wet: > 35%.
- Adjust temperature readings based on ambient conditions.

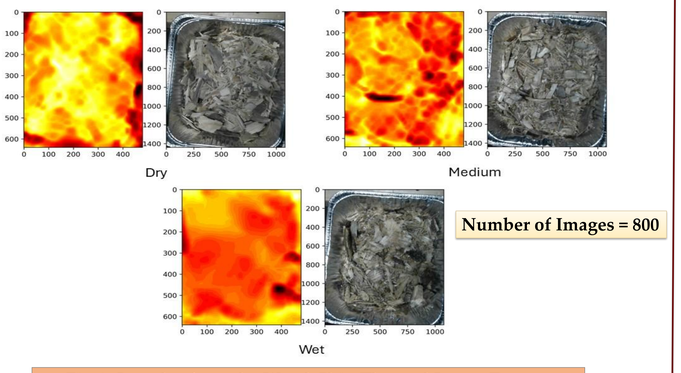


Fig 4. Samples from the Wood Chip Thermal Image Dataset

Moisture Content Prediction Models

Machine Learning Models
- Decision Tree
- Random Forest
- SVMs
- XGBoost

Deep Learning Models
- MLP
- DenseNet121

Fig 5. Flowchart of the Process

Results

T1. Model Performance Metrics (Without Temperature Adjustment)

Model	Accuracy	Precision	Recall	F1-Score
Decision Tree	0.5122	0.5173	0.5122	0.5139
Random Forest	**0.6585**	0.6619	**0.6585**	**0.6533**
SVM	0.5707	**0.6741**	0.5707	0.5381
XGBoost	0.6146	0.6176	0.6146	0.6076
MLP	0.5805	0.5948	0.5805	0.5778
DenseNet121	0.5463	0.5911	0.5463	0.4981

T2. Model Performance Metrics (With Temperature Adjustment)

Model	Accuracy	Precision	Recall	F1-Score
Decision Tree	0.5600	0.5626	0.5600	0.5581
Random Forest	**0.6700**	0.6785	**0.6700**	**0.6682**
SVM	0.5800	**0.6790**	0.5800	0.5520
XGBoost	0.6650	0.6675	0.6650	0.6588
MLP	0.6100	0.6268	0.6100	0.5954
DenseNet121	0.5550	0.6391	0.5550	0.5016

T3. Model Improvement Summary comparison with ambient temperature and humidity data

Model	Accuracy without adjustment	Accuracy with adjustment	Improvement (%)
Decision Tree	0.5122	0.5600	**9.3**
Random Forest	**0.6585**	**0.6700**	1.7
SVM	0.5707	0.5800	1.6
XGBoost	0.6146	0.6650	8.2
MLP	0.5805	0.6100	5.1
DenseNet121	0.5463	0.5550	1.6

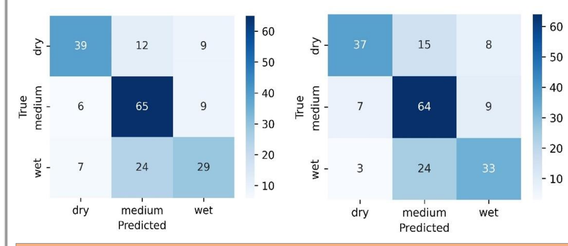


Fig 6. Confusion Matrix of the Predictions from Top Two Highest Performing Models on adjusted data: XGBoost (Left) and Random Forest (Right)

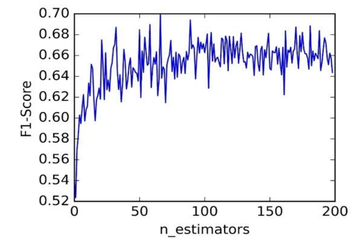


Fig 7. Hyperparameter Tuning of Random Forest Model - F1-Score Variation with Number of Estimators.

Conclusion and Future Research Directions

Conclusions

- **Accuracy Improvement:** Temperature and humidity adjustments based on ambient conditions improved model accuracy, with Random Forest achieving 67%.
- **Environmental Adjustments:** Adjusting thermal image temperatures for ambient conditions was crucial for model performance, emphasizing environmental considerations.
- **Comprehensive Evaluation:** Using metrics like accuracy, precision, recall, and F1-score gave detailed insights into each model's strengths and limitations.

Future Research Directions

- Integrate the machine vision tool with IoT for real-time monitoring and control of wood chip moisture content in industrial settings.
- Investigate the benefits of advanced moisture measurement systems, focusing on energy savings, lower emissions, and cost reductions in biofuel and pulp production.
- Expand the tool to assess other quality indicators like ash content and particle size distribution, enhancing its utility in biofuel and the pulp & paper industry.

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References

For the references, please scan this QR code:

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