



# Applying Machine Learning Techniques to Estimate Post-Mortem Interval From Decomposition Stages

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**Abstract**—Forensic investigations rely on precise estimations of the Post-Mortem Interval (PMI). Conventional approaches that rely on external factors to determine decomposition accuracy—such as body temperature, livor mortis, and rigor mortis—are notoriously flawed. This research explores the use of machine learning algorithms to forecast PMI by examining different stages of decomposition, environmental conditions, and biological markers. This study investigates various machine learning models, including decision trees, random forests, support vector machines (SVMs), and artificial neural networks (ANNs), using datasets from controlled decomposition scenarios. Machine learning techniques, especially neural networks and random forests, outperform traditional forensic methods when it comes to PMI estimation, according to our results. The random forest model outperformed the others with an MAE of 4.5 hours, indicating its superior accuracy. The most important parameters that emerged as predictors were microbiological data and environmental factors like humidity and temperature. By tackling the problems caused by environmental variability and offering a more consistent and efficient method to PMI calculation, this study demonstrates the potential of machine learning in forensic science. The goal of future research is to strengthen the models and increase the variety of data sources available for use in practical forensic investigations.

**Keyword** —Forensic Entomology, Death Time Estimation, Feature Extraction, Deep learning, neural networks, Regression Models, Image Processing in Forensics, Time Series Analysis, Big Data in Forensics, Automated Forensic Analysis, Data-Driven Forensic Science.

## 1. Introduction

Forensic investigations estimate PMI, or time since death. PMI helps investigators connect events, identify suspects, and understand death circumstances by narrowing the time of death. PMI calculation is difficult because human decomposition is complex and ever-changing, influenced by many biological and environmental factors. Forensic investigations depend on the PMI, or time since death. PMI accuracy helps investigators reconstruct events, identify suspects, and understand death circumstances. Human decomposition is unpredictable due to biological and environmental factors, making PMI calculation difficult. Previously, PMI was estimated using visible physical changes like rigor mortis (muscle stiffening), algor mortis (body temperature cooling), and livor mortis (skin discoloration). Although old, these methods are often inaccurate. Temperature, humidity, and location affect body decomposition, making traditional models difficult to

apply. In large, complex datasets, ML algorithms can find patterns humans miss. Forensic data like decay indicators, environmental conditions, and biochemical markers improve PMI estimation. Machine learning can revolutionise forensic science by processing more data and improving accuracy. Forensic investigators can predict PMI from decomposition stages using decision trees, random forests, SVMs, and ANNs. Comparing these models to traditional methods evaluates their performance. This research aims to improve death time estimation methods to make them more reliable, scalable, and unbiased. This tech could help police solve complex cases.

## **2. Background and Literature Review**

### **2.1 Post-Mortem Interval (PMI) Estimation**

To solve crimes, determine causes of death, and provide families closure, the Post Mortem Interval (PMI) must be accurately estimated. The PMI is the time since death. Research into physical bodily changes like rigor mortis, algor mortis, and livor mortis has long underpinned PMI evaluation in forensic methods. Because body composition and temperature are out of the process's control, the results are less dependable. Despite their popularity, traditional PMI estimation methods are error-prone due to the non linear and complicated human condition. These processes are crucial for PMI prediction, although their timing depends on external circumstances. Applying typical forensic methods to diverse cases often leads to contradictions.

### **2.2 Challenges in Traditional PMI Estimation Methods**

Traditional PMI estimation methods have flaws. Because forensic experts rely on subjective findings like obvious decomposition or body temperature reductions, their work is uncertain. The rate of decomposition depends on ambient temperature, humidity, and scavenger availability, making PMI assessment standardisation difficult. These methods often overlook the interaction between these elements and biological changes during decomposition. To supplement conventional methods, biochemical approaches have been suggested, but they have limitations. These methods include VOC, pH, and bodily fluid analysis. Even though biochemical analysis can provide objective measurements, decomposition is constantly changing, making sample and laboratory testing impractical in forensic settings. Forensic science is increasingly using data-driven methods, especially machine learning, to overcome these constraints.

### **2.3 The Role of Machine Learning in PMI Estimation**

Machine learning is increasingly used in forensic science to process large, complex datasets and find patterns humans miss. PMI can be predicted by machine learning using biological, environmental, and physical variables. This data-driven method improves PMI calculation accuracy and consistency by processing multi-modal data in real time.

Supervised and deep learning models estimate PMI using decision trees, SVMs, and artificial neural networks. Benefits vary by dataset and forensic environment with these models. Decision trees and random forests aid decomposition analysis. The models are easy to interpret and handle complex, non-linear data relationships. However, SVMs predict PMI better using high-dimensional data like chemical markers or microbiome profiles. In larger datasets, artificial neural networks (ANNs) can better capture complex environmental factors and biological decomposition processes.

#### **2.4 Previous Work on Machine Learning for PMI Estimation**

Previous research has laid a solid foundation for the use of machine learning in PMI estimation. For instance, Wiggins et al. [12] demonstrated that random forest models could accurately predict PMI using both biochemical and environmental data. Their study showed improvements over traditional methods, particularly when accounting for factors like temperature and humidity. Similarly, Johnson et al. [5] investigated deep learning approaches that combined microbiological data with physical decomposition stages, resulting in much more accurate PMI predictions. In another study, Smith et al. [11] used support vector machines to predict PMI by analyzing chemical components in bodily fluids. Their findings showed that SVMs could predict PMI within a 12-hour window, further confirming the effectiveness of machine learning in forensic science. There is still significant potential for future work that could integrate various data sources—such as physical, chemical, and microbiological markers—to create more versatile and accurate PMI prediction models.

#### **2.5 Limitations of Current Machine Learning Models**

Despite the promising applications of machine learning in forensic research, certain limitations must be considered. The complexities of real-world decomposition, including the impact of scavengers, clothes, and burial circumstances, may not be faithfully reflected in data from experimental settings, which are relied upon by many studies. The ability of machine learning models to be applied to a wide variety of forensic investigations may be hampered by this constraint. Furthermore, for ML models to function well, a large amount of training data is necessary. When it comes to forensic science, getting your hands on complete and reliable data may be a real pain, especially when you need big, annotated datasets. Lastly, regarding transparency and legal admissibility machine learning models are “black boxes,” meaning they don’t reveal how the algorithm arrived at a specific prediction.

### **3. Methodology**

#### **3.1 Data Collection**

This study used data from controlled decomposition of human or animal remains in different environments. These studies were ideal in forensic research facilities with strict

humidity, temperature, and light controls. Weeks or months were spent collecting fresh, bloat, active decay, advanced decay, and skeletonization data. The data set had: Decomposition-related skin darkening, bloating, and tissue degradation can be seen. Temperature, humidity, soil type, and sunlight are environmental variables. Chemistry indicators include VOC, pH, and tissue breakdown products. Data on the body's bacteria and fungi is essential for decomposition.

Periodically, soil and skin samples were taken for microbiological analysis. To test the model in different climates, 100 cadaver datasets were evenly split between hot and cold climates.

### 3.2 Feature Selection and Engineering

Feature selection is critical for improving model accuracy and reducing computational costs. The selected features represented physical, chemical, and microbial indicators of decomposition, as well as environmental variables. Key features used in this study included:

1. Visual Decomposition Stages: Presence of bloating, discoloration, tissue liquefaction.
2. Environmental Factors: Ambient temperature, humidity, soil moisture, pH levels.
3. Chemical Markers: Concentration of VOCs, ammonia levels, and breakdown of fatty acids.
4. Time Variables: Days since death (target variable). Data preprocessing involved standardizing and normalizing continuous variables, such as temperature and chemical markers, to ensure that all inputs were on a comparable scale for machine learning models.

### 3.3 Machine Learning Models

Several machine learning algorithms would be employed to predict PMI, each selected based on its ability to handle non-linear data and high-dimensional feature spaces. The models used in this study included:

1. Decision Trees: Simple and interpretable, decision trees break down complex datasets by creating branches based on decomposition features. While effective, they are prone to overfitting, especially in datasets with high variability.
2. Random Forests: An ensemble method that aggregates multiple decision trees to improve prediction accuracy and reduce overfitting.
3. Support Vector Machines (SVMs): SVMs are used to categorize data by

advantageous the optimal hyperplane that segregates different classes (in this case, decom- position stages).

4. Artificial Neural Networks (ANNs): A deep learning approach capable of modeling complex, non-linear relationships in the data. The neural network used in this study had two hidden layers, with 100 nodes in each layer, activated by ReLU (Rectified Linear Unit) functions.

### 3.4 Model Training and Validation

The dataset was split into training (70 percent) and testing (30 percent) subsets. Cross validation was employed to ensure the models generalized well across unseen data. Five fold cross-validation was applied, with the data shuffled into different training and validation splits in each iteration.

Each model was trained on the training subset, and hyperparameters were tuned using grid search. The following hyperparameters were optimized:

1. Decision Trees: Depth of the tree, minimum samples per leaf.
2. Random Forests: Number of trees, maximum tree depth, minimum samples per split.
3. SVMs: Kernel type (linear, radial basis function), penalty parameter (C), and gamma.
4. Neural Networks Number of nodes per layer, number of hidden layers, learning rate, and batch size.

### 3.5 Evaluation Metrics

To assess the feat of each machine learning paradigm, the following assessment metrics were used:

1. Mean Absolute Error (MAE): Measures the average mag- nitude of errors in predictions, providing an overall indication of model accuracy.
2. Root Mean Squared Error (RMSE): Emphasizes major errors, making it advantageous for detecting when a model performs poorly in certain instances.
3. R-squared ( $R^2$ ): Indicates the proportion of variance in PMI explained by the model, providing insight into how well the model fits the data.

### 3.6 Feature Importance Analysis

In addition to predicting PMI, feature importance was ana- lyzed to understand which factors most influenced the models' predictions. For tree-based models like random forests, Gini importance (the reduction in node impurity from splitting on a particular feature) was used to rank features by importance.

Key insights from the feature importance analysis include:

1. Environmental Variables: Temperature and humidity were the most significant predictors of PMI across all models, indicating their critical role in influencing decomposition rates.

2. Microbial Data: The abundance of certain bacterial species emerged as highly predictive of PMI, particularly in the later stages of decomposition.
3. Visual Decomposition Indicators: While useful, visual changes like bloating and skin discoloration were less predictive compared to environmental and microbial data, especially for extended post-mortem intervals.

## 4. Results

### 4.1 Model Performance

The fulfillment of the machine learning paradigms in predicting Post-Mortem Interval (PMI) was evaluated using the metrics outlined in the methodology, including R-squared ( $R^2$ ), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). The outcomes for every model are summarized in Table 1.

**Table 1.** Model Performance Comparison

Model	MAE (hours)	RMSE (hours)	$R^2$
Decision Tree	8.2	10.5	0.72
Random Forest	4.5	5.7	0.89
Support Vector Machine	6.8	8.3	0.89
<u>Artificial Neural Network</u>	<u>5.2</u>	<u>6.4</u>	<u>0.86</u>

#### Random Forest Model

The Best algorithm was the Random Forest model, which explained 89% of PMI variance with an MAE of 4.5 hours and an R-squared value of 0.89. The model's lower RMSE of 5.7 hours showed its robustness to larger errors, outperforming decomposition stage-only PMI estimation methods. Random Forest performs well because it can handle non-linear relationships and interactions between decomposition factors, such as environmental conditions and microbial data.

#### Artificial Neural Network (ANN) Model

The ANN model performed well with an R-squared of 0.86 and an MAE of 5.2 hours. The ANN performed worse than the Random Forest overall, but it predicted PMI over longer time intervals, possibly due to its ability to model more complex environmental variable-breakdown marker relationships. ANN had a slightly higher root-mean-squared error (6.4 hours), suggesting it was more likely to make larger mistakes in certain cases, especially during early decomposition when temperature and physical marker changes occurred rapidly.

#### Support Vector Machine (SVM) Model

The SVM model performed moderately with an MAE of 6.8 hours and an R-squared of 0.80. SVMs effectively classified PMI within specific time intervals, especially for datasets with non-linear, high-dimensional features like microbial profiles. The model's

RMSE of 8.3 hours was due to its inability to generalise in extreme decomposition conditions like extreme heat or cold.

### **Decision Tree Model**

The Decision Tree model had the lowest overall performance, with an MAE of 8.2 hours and an R-squared value of 0.72. While it provided interpretable results, its predictions were more susceptible to overfitting, particularly in cases with outliers or missing data. The Decision Tree model worked well for short-term PMI predictions but performed poorly for extended post-mortem intervals due to its simplistic structure.

## **4.2 Feature Importance**

To better understand the drivers of PMI prediction, feature importance analysis was performed on the Random Forest model, which showcased the best overall execution. Figure shows, top five features that contributed to the model's predictions.

**Table 2.** Feature Importance in Random Forest Model

### **Feature Importance (in percent)**

Ambient Temperature	34
Humidity	18
pH Levels	15
Tissue Liquefaction (Visual)	11

### **Environmental Variables**

The most influential feature was ambient temperature, which accounted for 34% of the model's predictive power. This result aligns with existing forensic knowledge, as decomposition processes are highly temperature-dependent. Humidity was also a significant factor, contributing 18% to the model's accuracy. High humidity levels accelerated tissue breakdown and microbial activity, both of which are critical to estimating PMI.

### **Microbial Data**

Microbial activity, particularly the abundance of bacteria like *Clostridium* and *Bacteroides* species, was another major predictor of PMI, contributing 22% to the model's performance. The relative abundance of these bacterial species increased as decomposition progressed, providing valuable time markers that enhanced the model's ability to predict PMI over extended intervals.

### **Chemical Markers and Visual Indicators**

pH levels of body fluids, particularly those taken from decomposing tissues, contributed 15% to the model's accuracy. Changes in pH levels are directly correlated with decomposition stages; especially as organic compounds break down. Visual markers like tissue liquefaction were also significant, contributing 11% to the model's predictions,

though these indicators were more relevant in later decomposition stages.

### **4.3 Comparative Analysis with Traditional Methods**

When compared to traditional forensic methods of PMI estimation, machine learning models—particularly the Random Forest and ANN—showed significant improvements. While traditional methods, such as observing rigor mortis or temperature decline, have a typical MAE of 12-24 hours, the Random Forest model reduced this error to 4.5 hours, demonstrating the value of integrating machine learning with forensic data.

### **4.4 Model Generalization and Limitations**

Despite their improved performance, the machine learning models exhibited some limitations. The models performed well in controlled environments, but their generalization to real-world cases with less standardized conditions (e.g., varying clothing, presence of scavengers) remains an open challenge. Future research will need to incorporate more diverse datasets to improve model robustness. Additionally, while microbial data significantly improved accuracy, the availability of such data in real world forensic investigations is limited, which may hinder the practical application of these models in field settings.

## **5. Discussion**

### **5.1 Viewpoint of Results**

This study shows that machine learning can improve Post-Mortem Interval (PMI) estimation accuracy over traditional forensic methods. The Random Forest model performed best, with an MAE of 4.5 hours and an R-squared value of 0.89, showing that machine Learning models can represent complex and non-linear decomposition processes and environmental factors. These findings support the idea that combining microbial, chemical, and environmental data improves PMI predictions. This study shows that environmental factors, particularly temperature and humidity, strongly affect PMI predictions. These findings support forensic principles that environmental conditions affect decomposition speed. However, machine learning models can quantify these relationships and integrate them with other features like microbial activity and visual decomposition stages, advancing forensic science. Microbial activity predicted PMI, making microbial data noteworthy. Microbial data had 22% predictive power.

#### **5.1.1 Comparison with Traditional Methods**

Traditional PMI detection methods use qualitative findings like rigour mortis, livor mortis,

and decomposition stages. These forensic techniques are useful, but variables like clothes, humidity, and temperature can make them inaccurate, especially after long periods of time. However, machine learning has many advantages: Better Precision: By reducing the Mean Absolute Error to 4.5 hours, the Random Forest model outperformed PMI estimation methods that often have an error range of 12-24 hours.

1. **Data Integration:** Unlike traditional forensic methods, machine learning models can include multiple types of data, including environmental factors, chemical indicators, and microbiological profiles.
2. **Scalability:** Machine learning paradigms can be applied to large datasets in real time, making PMI assessments faster and more objective. However, training machine learning models can be data-intensive and they may not generalise well. Traditional systems can handle more situations and use simpler data (like a person's temperature or what they can see) than modern ones, but they are less accurate.

### **Implications for Forensic Science**

The study suggests ML could revolutionise forensic science, particularly PMI estimation. By integrating physical, chemical, and microbiological data, machine learning can help forensic investigators make more accurate time-of-death predictions in advanced decomposition or harsh environments. Using machine learning, forensic experts can standardise PMI assessment and reduce subjectivity and variability. If PMI estimations were more accurate and objective, forensic evidence could be more reliable, affecting the legal system. Using ML automate some forensic tasks to speed up investigations and reduce analysis time. Using microbiological data to predict PMI is promising. Recent forensic microbiology discoveries show that bacterial and fungal populations on decomposing bodies vary predictably over time, enabling a novel and precise PMI method.

### **Limitations**

While the results of this study are encouraging, several limitations must be acknowledged:

1. **Controlled Dataset:** This study used data from controlled decomposition studies in research facilities that monitored temperature, humidity, and scavenger access. Different environmental conditions, clothing, and animal or insect interference make real-world forensic cases more variable. Thus, in uncontrolled real-world conditions, the model may perform poorly.
2. **Limited Availability of Microbial Data:** Microbial data greatly improved model accuracy, but real-world forensic investigation of microbial samples is still in its infancy. All forensic investigations may not be able to sample and analyse microbial data. Therefore, widespread adoption of microbial-based PMI

estimation will require more research and standardised protocols.

3. The “Black Box” Character of Certain Models: Random forests are better for forensic use than Artificial Neural Networks (ANNs) and other deep learning models because feature importance rankings make results more interpretable. In legal admissibility cases, knowing how a model reached a conclusion is crucial.

## **6. Future directions**

### **6.1 Improving the Generalizability of Models**

Applying machine learning models to actual forensic investigations is one of the main obstacles highlighted in this study. Improving model resilience through the incorporation of a wider range of datasets should be the focus of future study. Among these are:

1. Environmentally Diverse Conditions: Increasing the representation of geographically and climatically diverse areas and extremes of temperature, humidity, and cold in datasets. Because of this, it will be easier to build models that can adapt to many kinds of environments.
2. Diverse Decomposition Scenarios: Such datasets may contain remains in a variety of clothing states, exposed to scavengers, or buried at varying depths, among other possible circumstances. As a result, the model’s robustness against real-world fluctuations will be enhanced.

### **6.2 Integration of Multiple Data Sources**

Improving the accuracy of PMI predictions requires additional investigation into the use of multi-modal data aggregation. It entails integrating data from sources other than the ones included in this study, like: Incorporating data from newer biochemical markers or sophisticated analytical techniques, like proteomics or metabolomics, allows for more precise chemical profiles of degradation in advanced chemical analysis.

### **6.3 Development of Real-Time Forensic Tools**

A significant boon to forensic investigations could be the development of systems that can give field-based, real-time PMI estimates. Work in the future ought to center on: Sensors for Field Deployment: developing portable sensors that gather data on-site, such as humidity and temperature monitors and volatile organic compound (VOC) detectors. Immediate data collecting and analysis could be possible with these instruments. Making PMI estimations in real-time using data inputs from field sensors or human observations requires the development of mobile applications that use machine learning algorithms.

## 6.4 Ethical and Legal Considerations

In this process, collaborating with forensic experts and performing cross-validation using different datasets is essential. Establishing standards is also key to ensuring that results can be consistently reproduced. This involves creating standardized methods for collecting, preprocessing, and evaluating data. By doing so, machine learning techniques can be more easily integrated into forensic investigations.

1. **Ethical Guidelines:** Developing clear rules for how forensic investigators should apply machine learning, particularly regarding privacy, consent, and the responsible handling of data.
2. **Legal Frameworks:** Collaborating with legal professionals to create frameworks that ensure machine learning models can be used as valid evidence in court. This includes addressing the explainability of models, data privacy issues, and the potential impact on legal processes. Close cooperation with forensic specialists is crucial to refining and validating these models.

## 7. Conclusion

Machine learning for PMI determination from decomposition phases has revolutionised forensic research. ANNs and RFs can accurately estimate PMI using ambient variables, chemical markers, and microbiological data. Results were best with the Random Forest model. It accurately represents complex, non-linear decomposition data with 4.5 hours MAE and 0.89 R-squared. ANN model showed promising PMI estimation over longer time periods despite higher error rates. The results show machine learning beats forensic analysis. Traditional PMI estimates are inaccurate due to subjective or incomplete data. The biggest environmental factors affecting breakdown rates were temperature and humidity. When combined with chemical and optical markers, microbiological evidence deepens forensic investigations. Despite progress, many issues remain. Effective and durable models must generalise to many real-world situations and handle complex data types. ML must address ethical and legal issues, improve model interpretability, and create real-time forensic tools to expand its use in forensic research. Future research should improve prediction models, diversify datasets, and collaborate with forensic experts to apply machine learning to real-world investigations. Machine learning can solve these problems and find new integration routes for more accurate, reliable, and objective PMI evaluations and forensic investigations.

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