International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 21s, 2025
https://theaspd.com/index.php

Time-Since-Death Estimation: A Review Of Ai Applications In Forensic Postmortem Interval Analysis

Dr Harsh[1], Tarun Kumar Singh[2], Dr Ashok Sagar[3], Dr. Upender Kishore[4]
[1]Assistant professor, Department of forensic medicine
Teerthanker Mahaveer Medical College & Research Centre Moradabad Up 244001
harsh3813@gmail.com
[2]Assistant Professor, Santosh Medical College, Ghaziabad, Uttar Pradesh
Orcid 0009-0009-8122-7381, tkumarsingh@gmail.com
[3]Professor & HOD, Department of forensic medicine, Santosh Medical College, Ghaziabad, Uttar Pradesh
[4]Director Prof. & Head, Department of Forensic Medicine, Dr. Baba Sahab Ambedkar Medical College & Hospital, New Delhi, upenderkishore@yahoo.in

Abstract:
Estimation of the postmortem interval (PMI) is an essential but difficult part of forensic analysis that has hitherto been based on subjective, frequently inaccurate markers. The recent developments in Artificial Intelligence (AI), especially Machine Learning (ML) and Deep Learning (DL), have accelerated a revolution in PMI estimation through the possibility of combining and processing various high-dimensional datasets. This paper discusses the fundamental concepts in AI that are being used for PMI estimation, including describing supervised and unsupervised learning models, neural networks, and convolutional and recurrent structures with specific orientations to process complex biological, chemical, and imaging data. It also discusses the contribution of multimodal data such as biochemical markers, transcriptomics, microbiomes, imaging, and environmental inputs in the improvement of accuracy and robustness of AI-based PMI models. Main research findings are examined, including the better performance of AI models like Artificial Neural Networks and Random Forests compared to conventional forensic practices. Notwithstanding these developments, issues remain, most notably around data availability, standardization, validation, and ethical implications related to the interpretability and implementation of AI in judicial proceedings. The article finishes with an appeal for more collaborative, standardized, and ethically informed research to move AI-based PMI estimation from experimental potential to operational forensic actuality.
Keywords: *Machine Learning, Deep Learning, Time Since Death, Thanatochemistry, Thanatomicrobiome.*

INTRODUCTION

Estimation of the postmortem interval, or time since death, is one of the most important and continually challenging activities in forensic science. Precise estimation of PMI is no mere academic goal; it is a critical part of legal investigation, used to determine timelines, validate or discredit alibis, and assist with the identification of unidentified remains, particularly in late stages of decomposition [1, 2, 3, 4]. In this regard, the PMI serves as an important temporal anchor, against which forensic accounts are built and evidence is read.

Forensic practitioners traditionally relied on a series of visible postmortem changes to estimate PMI. These include early signs such as algor mortis (cooling of the body), livor mortis (settlement of the blood), and rigor mortis (stiffening of the muscles), usually within the initial 24–72 hours [3]. Outside of this window, investigators review decomposition phenomena like autolysis and putrefaction, apply forensic entomology to review insect colonization, or evaluate biochemical markers within body fluids such as vitreous humor [3, 5]. While these methods form the basis of forensic practice, they are by no means faultless. Their accuracy is highly sensitive to numerous variables, including the deceased's age, body condition, and the environmental context—factors such as temperature, humidity, clothing, or whether the body was buried or exposed can significantly alter decomposition timelines [3, 6].

In addition, classical PMI estimation is usually highly dependent on experience, prone to subjective bias, and loses accuracy with increasing time post-mortem [1, 7]. Studies have demonstrated that although short PMI estimates can be fairly reliable, they increase significantly in error for durations beyond a certain length [8]. This uncertainty has generated a pressing need for more objective, data-supported methods for improving both the validity and range of PMI evaluation.

Herein, the development of Artificial Intelligence (AI)—particularly Machine Learning (ML) and Deep Learning (DL)—has started to bring transformative possibilities to forensic science. AI can leverage big datasets, identify intricate, non-linear patterns, and integrate varied types of input data well, which suits the task of PMI estimation [4, 9]. Instead of replacing the experts in forensic science, AI technology is seen to supplement their analyses with quicker, unbiased findings drawn from a wider range of biological, chemical, microbial, and environmental markers [9, 10].

This review seeks to critically examine the expanding overlap between AI and PMI estimation. It will consider traditional approaches and their limitations, the range of AI methodologies being used, the data types being used, and the performance and ethical issues involved in using these methods. Through the integration of existing literature and the establishment of areas for future investigation, the review hopes to explain how AI can enhance the accuracy and uniformity of time-of-death predictions, better supporting forensic investigations and judicial decisions.

Traditional Techniques for PMI Estimation: Principles and Challenges

The search to identify the time elapsed since death is as ancient as forensic examination itself. Across centuries, professionals have evolved and honed an array of techniques centered on observable, sequential alterations that develop within a human body after death. These old methods, though the basis for forensic pathology, are a heterogeneous group of methods each with their own scientific underpinning, window of relevance, and built-in set of problems [3]. Knowledge of these tried and true methods as well as their limitations is paramount for a better appreciation of the background into which newer, AI-based methods are entering.

Early Postmortem Changes: The Classic Triad

Even after death, a chain of physical events starts, commonly termed as the early postmortem period. The best-known signs during this stage are algor mortis, livor mortis, and rigor mortis.

- Algor Mortis: It is the cooling of the body postmortem. Following death, metabolic activities stop, and the body slowly comes to a balance with the surrounding environmental temperature. While the general principle is straightforward – a body cools over time – the rate of cooling is far from constant. It is largely determined by such factors as the temperature at death (which will be raised by fever or exercise), body size and fat composition (fatty tissue is an insulator), clothes or coverings, movement of air, humidity, and immersion in water [1, 3]. Several formulae and nomograms have been created to predict heat loss, but the variability of factors involved in making an accurate PMI estimation based only on temperature is difficult after the body has equilibrated with ambient temperature.
- Livor Mortis (Lividity): After circulatory collapse, red blood cells gravitate to the lower regions of the body due to gravity and settle in the dependent regions of the body, producing a purplish-red coloration of the skin referred to as livor mortis or lividity [3]. Lividity usually becomes apparent within 2-30 minutes of death, develops quite well in 6-8 hours, and attains maximum intensity at 12 hours. More importantly, lividity sets or "fixes" after some time (typically 8-12 hours) in that discoloration will not change even if the body's position is altered. The presence, color (cherry-red in carbon monoxide poisoning, for instance), pattern, and fixity of livor mortis may give clues regarding the PMI and whether the body was relocated after death. But its development is also influenced by room temperature and some medical conditions.
- Rigor Mortis: This process consists of the stiffening of muscles after death due to the exhaustion of adenosine triphosphate (ATP), which is required for the relaxation of muscles [3]. Rigor usually sets in in the smaller muscles (such as the jaw and eyelids) within 2-4 hours, spreads to the major muscles, is established in the entire body by 6-12 hours, lasts 24-36 hours, and then slowly disappears as muscle proteins start to break down during decomposition. Onset, duration, and resolution of rigor mortis vary greatly, being much affected by the activity level before death, room temperature (heat speeds up rigor, cold retards it), and specific modes of death or poisoning [3]. Although the order is to be expected, timing is notoriously uncertain for reliable PMI determination outside of a wide window.

Later Postmortem Changes: Decomposition and Entomology

When the PMI continues past the first day or two, the decomposition processes are the major cues.

- Decomposition: This multifaceted process is made up of two key mechanisms: autolysis (self-destruction by the body's own enzymes) and putrefaction (tissue breakdown by bacteria and other microbes) [3]. Decomposition occurs in visually recognizable stages, commonly divided into fresh, bloated (because of gas formation by bacteria), active decay (characterized by liquefaction of tissue and pungent odors), advanced decay (tissues mostly dissolved), and dry remains/skeletonization [5]. Decomposition rate is greatly affected by environmental conditions, specifically temperature and humidity, but also by insects,

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 21s, 2025
https://theaspd.com/index.php
burial, clothing, trauma, and the body's own properties [1, 3]. Although the stages of decomposition give a general time frame, it is hard to convert these stages into a specific PMI because of this variability.
• Forensic Entomology: The analysis of insects, most notably blowflies and beetles, which infest decomposing corpses is a basis for subsequent PMI estimation [3, 5]. Insects arrive on a corpse in regular waves or successions, which are drawn by the varied stages of decomposition. By determining the species involved and examining their developmental stages (egg, larva/maggot instars, pupa, adult), forensic entomologists can approximate the minimum time since colonization, which usually follows closely with the minimum PMI, particularly in the first few weeks or months following death [3]. This technique necessitates expert proficiency in insect identification and familiarity with insect development rates under different environmental conditions (particularly temperature). Its reliability is subject to variables such as insect access to the body and the presence of appropriate local entomological information.
Biochemical and Other Techniques
Apart from gross physical and entomological observation, several biochemical analyses have been investigated:
• Vitreous Humor Potassium: The potassium ion concentration of the vitreous humor (the jelly in the eyeball) rises relatively predictably following death [3]. This test is one of the more reliable early PMI biochemical markers (up to several days), but is also variable and needs careful sample treatment and examination.
• Other Biochemical Markers: Alterations of cerebrospinal fluid (CSF) components, enzyme levels, and breakdown of certain proteins or nucleic acids (DNA/RNA) have also been explored, but are usually lacking in consistency or utility for everyday use [3, 5].
• Supravital Reactions: Determination of the latent excitability of muscles or pupils to electrical or chemical stimulation may yield information during the very early PMI (minutes to hours), but the reactions terminate quite rapidly [5].
General Challenges of Conventional Techniques
In spite of the numerous conventional techniques, some inherent challenges restrict their accuracy and reproducibility, especially at higher PMI:
1.Environmental Sensitivity: Almost all conventional techniques are sensitive to the environment, particularly temperature, humidity, and accessibility (e.g., burial, garments, water immersion) [1,3].
2.Intrinsic Variability: Individual-specific factors, including age, body mass index, cause of death, and underlying illnesses, can greatly influence the rate of postmortem changes [1].
3.Subjectivity: Stages such as rigor mortis or level of decomposition may require subjective interpretation by the examiner during assessment.
4.Reduction in Accuracy with Time: The accuracy of most of the classical methods also falls substantially with the passage of time as the PMI is beyond the initial days [1, 6]. Determining PMI in skeletonized bodies or over periods of months or years is based largely on less accurate determinants such as entomology or taphonomic alteration.
5.Teacher Expertise Required: Techniques such as forensic entomology demand very specialized knowledge and training.
It is this terrain of established but inaccurate methods, combined with the compelling imperative to improve the accuracy of forensic work, that has opened the door to investigating the potential of Artificial Intelligence to examine the complex, multifaceted data involved in postmortem changes and deliver more solid estimations of time since death.

Artificial Intelligence Paradigms and Data Sources in PMI Estimation

The intrinsic complexity and multifactorial nature of postmortem changes, which derange conventional estimation methods, are exactly the kind of challenge for which Artificial Intelligence (AI) can provide substantial benefits. AI, specifically its branches of Machine Learning (ML) and Deep Learning (DL), is a set of computational methods that include algorithms to learn patterns, make predictions, and draw conclusions from data, often beyond human levels in terms of speed and complexity management [2,4]. In PMI estimation, AI is not seen as a substitute for forensic expertise but as an analytical tool with great potential for combining heterogeneous data streams and simulating subtle, time-dependent chemical and biological processes that take place after death [2,4].

Core AI Concepts: Machine Learning and Deep Learning

Fundamentally, the use of AI in PMI estimation is mostly Machine Learning. The ML algorithms are learned with known PMI values along with respective measurements (features) from postmortem samples

or observations. The intent is that the algorithm learns the correlation between the features and the PMI so that it may make predictions for new, unseen cases on the basis of their feature measurements.
• Machine Learning (ML): This encompasses a wide range of algorithms with the ability to learn from data without being specifically programmed for every particular task. Typical methods used in PMI studies are [2, 8]:
• Supervised Learning: The most popular paradigm used in PMI estimation, where the algorithm learns from labeled examples (i.e., samples whose PMI is known). Principal tasks are:
• Regression: To predict a continuous target, e.g., the PMI in hours or days. Algorithms such as Linear Regression, Polynomial Regression, Support Vector Regression (SVR), and tree-based regression models (e.g., Random Forest Regression) are utilized.
• Classification: To predict a category, e.g., to categorize PMI into discrete intervals (e.g., <24h, 24-72h, >72h). Algorithms such as Support Vector Machines (SVM), Decision Trees, Random Forests (RF), and k-Nearest Neighbors (kNN) are often utilized.
• Unsupervised Learning: Applied more infrequently for explicit PMI prediction but useful for exploratory data analysis and feature identification (e.g., finding clusters of samples with comparable biochemical profiles). Clustering algorithms such as k-Means belong to this type.
• Deep Learning (DL): A category of ML derived from Artificial Neural Networks (ANNs) with many layers (deep architectures). DL models can learn automatically hierarchies of feature representations from raw input data, which makes them especially powerful for rich data types such as images or sequential data [2].
• Artificial Neural Networks (ANNs): Basic DL models, commonly utilized for regression or classification applications with tabular data (e.g., biochemical measurements) [2,8].
• Convolutional Neural Networks (CNNs): Optimized for grid-like data, mostly images. CNNs in forensic science are used to examine medical imaging data (CT, MRI – also referred to as Virtopsy) or even photographic records of decomposition phases [1,2].
• Recurrent Neural Networks (RNNs): Optimized for sequential data, thus well adapted to examine time-series data, including patterns of RNA degradation or longitudinal variation of microbial communities [9].

Data Modalities Driving AI in PMI Research

The strength of AI models is that they can process and consolidate information from multiple sources. AI-based PMI estimation research takes advantage of a large variety of data modalities, echoing the dimensional character of postmortem changes [1, 2,4, 7]:
• Biochemical Markers: Measuring the varying levels of metabolites, electrolytes (such as potassium in vitreous humor), proteins, and enzymes in different body fluids (blood, CSF, vitreous humor) and organs (muscle, liver, brain) continues to be an important area of interest [1,7]. Methods such as mass spectrometry produce large quantities of data amenable to ML evaluation (frequently referred to as metabolomics or proteomics) [1].
• Genetic and Transcriptomic Information: The degradation profiles of nucleic acids, especially RNA (transcriptomics), exhibit time-dependent behavior that could be measured by methods such as RNA sequencing (RNA-Seq) and could be predicted by AI [3, 11]. DNA methylation profiles are also being investigated.
• Microbiome Information (Thanatomicrobiome): The makeup of body-onset and body-resident microbial communities (bacteria, fungi) shifts in a predictable manner following death as various species overgrow or disintegrate through decomposition. Examining the microbial profile (frequently through 16S rRNA or shotgun metagenomic sequencing) presents another valuable source of information for AI models [8].
• Imaging Data: Medical imaging modalities such as Computed Tomography (CT) and Magnetic Resonance Imaging (MRI), sometimes jointly termed as "Virtopsy" or postmortem computed tomography (PMCT), have the ability to image internal alterations related to decomposition. AI, particularly CNNs, can be used to image these pictures and detect subtle, time-dependent characteristics [1, 2]. Hyperspectral imaging is also a developing field.
• Physical Parameters: Ongoing observation of physical changes such as body temperature (extending algor mortis research), tissue electrical impedance, or physical measurements during bloating may yield quantitative information for AI models.

• Entomological Data: Although traditionally analyzed by experts, AI may be able to help in the identification of insect species or developmental stages from pictures or environmental information, supplementing conventional forensic entomology.

• Environmental Data: Direct integration of sensor data on ambient temperature, humidity, soil status, etc., into AI models is important for considering the tremendous impact of the environment on decomposition rates.

The ability of AI to potentially integrate these disparate data streams – combining biochemical profiles with microbial signatures, imaging features, and environmental context – holds the promise of creating more holistic and robust models for PMI estimation than achievable through any single traditional method alone.

Applications of AI in PMI Estimation: Current Research Landscape

The theoretical capability of Artificial Intelligence to deconstruct the intricacies of postmortem alteration is quickly moving into concrete research applications. Researchers are working aggressively to discover how different AI methods can simulate time-dependent change in a range of biological and physical modalities of data, with the goal of creating more precise and objective PMI estimations than ever before possible [2, 4]. The research environment today reflects a wide variety of methods, frequently using high-throughput approaches to create the large datasets necessary for successful machine learning.

Using the Molecular Clock: AI in Omics-Based Estimation of PMI

Maybe the most vibrant domain of AI usage in PMI research is dealing with large-scale molecular data, i.e., "omics." Such methods try to obtain complete pictures of the molecular condition of fluids and tissues at various times post-mortem.

• **Proteomics, Metabolomics, and Lipidomics**: Mass spectrometry (MS) is now a foundation technology that allows for the simultaneous identification and quantification of hundreds to thousands of proteins (proteomics), metabolites (metabolomics), and lipids (lipidomics) from postmortem samples [1]. AI, specifically ML algorithms, is required to navigate such data complexity. It has been demonstrated that there are predictable, time-dependent degradation patterns for many macromolecules [1]. For example, metabolomic and lipidomic signatures, showing alterations in small molecule levels upon the cessation of enzymatic activity and microbial activity, seem highly promising for quantifying shorter PMIs (in the first few days) [1, 7]. In contrast, proteins degrade relatively slowly and in a more predictable way over long times and thus proteomics might be a more appropriate method for longer PMIs [1, 3]. Muscle tissue has become a popularly studied substrate because it is relatively abundant and accessible, followed by the liver and bone [1]. Being aware of the merits and demerits of each layer of omics, scientists propose an integrated "Forensic omics" strategy, marrying proteomic, metabolomic, and lipidomic information to be able to potentially span a broader range of PMIs with improved precision [1]. Systematic reviews show a high emphasis on briefer PMIs (<7 days) in recent omics-based literature, with the need for increased numbers of studies examining medium (7–120 days) and extended (>120 days) intervals [13].

• **Transcriptomics (Degradation of RNA):** Degradation of RNA molecules following death also exhibits a fairly predictable trend, dependent upon cellular enzymes (RNases) and external conditions. AI algorithms, such as RNNs designed for sequential data, are being used to compare RNA sequencing (RNA-Seq) data between different tissues to identify specific RNA degradation profiles with PMI [3, 2]. RNA is potentially less stable than proteins in general, however, and may be limited in its use for longer PMIs or in adverse environmental conditions.

• **Thanatomicrobiome**: The microbial communities within the body change drastically following death, fueled by the fluctuating biochemical environment and the degradation of host barriers. High-throughput sequencing methods enable scientists to profile these microbial successions dynamically. AI programs are used to discover correlations between the structure and composition of the thanatomicrobiome (in the gut, on the skin, in organs) and the PMI [2]. This approach offers a unique window into the decomposition process but is also highly sensitive to environmental influences and initial microbial load.

AI Performance and Model Comparisons

In addition to investigating data modalities, studies are also actively exploring the performance of various AI models for predicting PMI. Although direct comparison is usually challenging because of differences in datasets, approaches, and performance measures, certain trends are converging:

• Advantage over Classical Methods: Several studies indicate that ML algorithms, especially methods such as Artificial Neural Networks (ANNs) and Random Forests (RF), can be superior to classical forensic techniques in terms of accuracy and precision in PMI estimation, especially in complex, multi-variable datasets [2, 10].

• Model-Specific Performance: Certain model structures exhibit different levels of success. In one study with direct comparison of ANN and RF for PMI estimation using specific features, it was observed that ANN consistently performed better, returning a higher coefficient of determination (R^2) and lower Mean Absolute Error (MAE) [12]. In another study, high accuracy of 93% was achieved by utilizing a multi-organ stacking model, where predictions were combined from models trained on data of different tissues [11].

• Accuracy Measures: Scholars usually quantify model performance with measures such as MAE (average error in predicted PMI), Root Mean Squared Error (RMSE), and R^2 (variance explained proportion). Although good results are obtained, consistently low error rates under various conditions and long PMIs are a major objective [1,9,11].

AI in Postmortem Imaging and Other Applications

AI is also gaining entry into the examination of imaging data and other forensic evidence pertinent to PMI:

• Virtopsy and Radiomics: Postmortem computed tomography (PMCT) and MRI enable the non-invasive imaging of internal structures and changes resulting from decomposition. AI, and particularly CNNs, can be programmed to analyze automatically these intricate images, extracting quantitative features (radiomics) that can potentially associate with PMI, potentially detecting subtle changes which are not seen through visual inspection only [2].

• Linked Forensic Applications: Though not explicitly PMI estimation, AI is likewise utilized in linked autopsy and crime scene examinations, including the estimation of weapon types based on wound patterns, toxicological examination, and assisting in forensic identification (e.g., face recognition, dental record matches), showing the wider incorporation of AI in forensic processes [2].

Implementation of AI in PMI estimation is an area of work that is changing fast. Existing research emphatically illustrates the practicality and potential value of the use of ML and DL to process various postmortem data. Translating these research results into proven, regularly usable forensic tools, though, involves overcoming considerable hurdles in relation to data standardization, model verification, and operational applicability.

Challenges, Limitations, and Ethical Considerations

In spite of the impressive promise and the accelerated progress in the use of Artificial Intelligence for the estimation of Postmortem Interval, the process of moving from the promising research results to established, routinely used forensic tools is faced with various considerable difficulties and limitations. In addition, the incorporation of AI into such a vital part of the legal framework requires scrupulous examination of the ethical implications.

Data-Related Hurdles

The most commonly mentioned barrier is possibly the access and the quality of the data used to train and validate strong AI models [13].

• Size and Scarcity: Establishing sound ML models, particularly deep learning methods, commonly demands extensive datasets. Obtaining large collections of human postmortem tissue with precisely determined PMIs and complete related data (environmental factors, subject details, cause of death) is inescapably challenging for reasons of logistics, ethics, and practicalities. Most existing research draws upon fairly limited datasets, frequently employing animal models, that could curtail the applicability of their results to human casework.

• Representativeness and Diversity: Data collections need to be sufficiently diverse to encompass the broad range of variables affecting decomposition. Models, when trained on data from one set of environments or populations, can fail when exposed to conditions or individuals with other physiological profiles. It is important that datasets be representative of the diverse situations found in actual forensic applications.

• Standardization: Absence of standardized methodologies for data collection, sample processing, analytical methods (e.g., a specific MS platform or sequencing approach), and reporting of results hinders comparison of results between studies or aggregation of data for larger meta-analyses [1]. Standardization of methods is crucial for cumulative knowledge generation and validation.

Methodological and Validation Challenges

Aside from data acquisition, the methodologies used in AI-based PMI research are under examination.

• Experimental Design and Rigor: Robust experimental design with appropriate controls and confounding variable consideration is essential. The nature of the postmortem process demands careful planning to be able to isolate the impact of time from other factors that may influence the results.

• Validation Strategies: Strong validation is essential for any diagnostic or predictive model that would be used forensically. Most studies base evaluation primarily on internal validation (model testing on a subset of the very same data used for training), which tends to overestimate performance. External validation, model testing on entirely independent datasets gathered under different circumstances or by other research groups, is needed to determine real-world applicability and robustness, but does not usually occur [13].

• Comparability of Studies: Variations in selected AI algorithms, feature selection procedures, performance metrics documented, and validation methods render direct comparisons of the effectiveness of various AI strategies difficult [1].

Model Interpretability and the "Black Box" Problem

Several high-performance AI models, especially intricate deep learning structures, are "black boxes" – their internal decision-making process is not readily comprehensible to humans [13]. This transparency issue is an important obstacle in the legal system, where grounds for expert opinions and scientific evidence have to be understandable and pass a test (e.g., under Daubert or Frye tests in the US). Even if a model shows excellent predictive performance, its admissibility in court could be blocked if the reasoning behind it is not easily expressible. Attempts at Explainable AI (XAI) seek to solve this, but training interpretable but highly accurate models for large and complex biological data is an ongoing area of research.

Accounting for Variability

Whereas AI is very good at pattern recognition, models still have to contend with the great variability in the decomposition process. Successfully modeling the impact of a wide range of environmental influences (temperature fluctuations, humidity, insect access, burial substrate) and endogenous individual influences (age, BMI, disease state, medications) on predictive models is still a challenging task [1,3]. Simplistic models tend to be unable to capture this variability and will predict poorly in non-standard cases.

Accuracy Limitations

Even though AI is intended to surpass conventional approaches, existing AI-based methods are not error-free and continue to suffer from prediction errors. While accuracy tends to decline as the PMI rises, obtaining the high level of accuracy necessary for legal certainty in all time scales and conditions continues to be a challenge [2,6]. Aiding in establishing tolerable margins of error for forensic purposes is also an important consideration.

Ethical Considerations

The incorporation of AI into the estimation of PMI poses significant ethical considerations [2, 4,]:

• AI as an Aid, Not Substitute: It is strongly argued that AI must be seen as a means of support for forensic experts, complementing their judgment and competence, and not replacing human control and interpretation [4]. Overuse of automated mechanisms without fair judgment from skilled professionals would open up opportunities for mistakes or miscarriage of justice.

• Bias and Fairness: AI systems are prone to biases in their training data. If the datasets underrepresent some groups of people or sets of environmental conditions, the learned models can perform unfairly or inaccurately to those groups or situations.

• Data Privacy and Security: Dealing with sensitive postmortem information calls for strong procedures for privacy protection and data security.

• Accountability and Responsibility: Establishing accountability when an AI-supported PMI estimate is in error needs to have defined frameworks. The algorithm, the data, the developer, or the expert interpreting should be held responsible.

• Trust and Integrity: Ensuring public and legal trust in forensic procedures demands that the usage of AI is communicated openly, along with its strengths and weaknesses [2].

Overcoming these complex issues – across data science, forensic practice, and ethics – is necessary to fully capitalize on the potential of AI in yielding credible and legally admissible estimates of the postmortem interval.

Future Directions

The use of Artificial Intelligence for Postmortem Interval estimation is obviously an area full of promise, but it is still in a fairly early stage of evolution. Conquering the present limitations and achieving the maximum potential of AI in this area will involve determined work in a number of crucial fields. Future research and development must seek the following directions:

1.Large, Standardized, and Diverse Dataset Development: Perhaps most importantly, this is the prerequisite that makes progress most likely to be achieved. Multilateral efforts are required to develop large-scale, multi-center databases of high-quality human postmortem data. These datasets should have well-determined PMIs, complete metadata (individual information, cause of death, detailed environmental information), and data produced by using standardized protocols for sample handling, processing, and analysis (e.g., precise omics platforms, imaging settings). Guaranteeing diversity according to populations, geographic location, and environments within these datasets is critical for developing strong and generalizable AI models [12]. Publically available benchmark datasets would promote research considerably and enable more insightful comparisons between different AI methods.

2.Exploration of Multi-modal Data Fusion Methods: Since decomposition is driven by numerous factors expressed in a variety of data types, combining data from multiple sources has huge potential for enhancing PMI accuracy and resilience. Future studies need to concentrate on building advanced AI models that can efficiently integrate data from various modalities – integrating, for example, biochemical markers from proteomics and metabolomics with thanatomicrobiome signatures, radiomic features from PMCT scans, and real-time sensor measurements from the environment [1, 3,]. Multi-modal solutions have a greater chance of better reflecting the integrated nature of postmortem alterations and supplying more stable estimates over various conditions and timescales.

3.Priority on Explainable AI (XAI): In order to close the gap between research and everyday forensic practice, especially in relation to admissibility in courts, future AI models for PMI estimation have to prioritize interpretability. Investigation into XAI methods designed for forensic data is important. Creating models that not only give a good PMI estimate but also provide insight as to why they came up with that estimate (e.g., identifying the most significant features or giving confidence scores) will be crucial to achieving acceptance and trust by forensic practitioners and the judiciary [12].

4.Enphasize Strong Validation and Longitudinal Research: Going one step ahead of internal validation, next-generation research will need to include strong external validation with independent datasets. Longitudinal investigations, following changes in the same subjects (mainly through animal models or special human taphonomy facilities) over long time scales and through controlled environmental fluctuations, are necessary to understand the temporal dynamics of postmortem change and to establish whether AI models have predictive validity over many years.

5.Field-Deployable Technology Development: Although omics and imaging methods in the laboratory are strong, what's desired by many applications is to create fast, portable, and inexpensive devices that can be deployed at the scene or even in resource-constrained environments. Work on miniaturized sensors, handheld spectrometers, and machine-learning algorithms that are optimized for field analysis might result in useful tools for initial PMI estimation in the field [1].

6.Enhancing Interdisciplinary Cooperation: Advancement in this area requires intense cooperation between forensic scientists (pathologists, anthropologists, entomologists), analytical chemists, molecular biologists, data scientists, AI researchers, statisticians, and legal experts [3]. Each group provides critical know-how, and enhancing fruitful communication and collaborative research endeavors will be fundamental to creating solutions that are scientifically valid, technologically viable, and legally sound.

7.Tuning Models to Particular Scenarios: Instead of attempting a general PMI model applicable everywhere, subsequent research could aim to create niche models tuned to particular scenarios, such as various environmental settings (e.g., aquatic settings, desert environments), particular tissue types, or varying PMI ranges (early vs. late). Designing models for particular scenarios might better predict results for those situations.

By following these directions, the scientific community is able to carefully handle the existing limitations and lay a better foundation for the trustworthy and ethical use of Artificial Intelligence in the vital endeavor of estimating the time since death and, therefore, improve the abilities of forensic investigation.

CONCLUSION

Determining the Postmortem Interval accurately continues to be a foundation of forensic practice, but conventional approaches, however valued their historical worth, are restricted by intrinsic limitations in precision, objectivity, and utility, especially with increasing elapsed time since death. The development of Artificial Intelligence provides promising new horizons, with the ability to use powerful computing resources to analyze the intricate, multifactorial biological and chemical phenomena that evolve following death to an unachievable heretofore level of sophistication [2, 3, 4,].

This review has mapped the terrain of AI's emergent application to PMI estimation. We have gone back to the basics and recognized the limitations of traditional methods, underscoring the imperative for innovation. We traversed the varied AI paradigms, mostly Machine Learning and Deep Learning, being utilized, and reviewed the wealth of data modalities – from in-depth omics profiles (proteomics, metabolomics, lipidomics, transcriptomics) and thanatomicrobiome signatures to sophisticated medical imaging (Virtopsy) and physical measurements – powering these smart algorithms [1, 2]. Existing studies are shown to exhibit real progress, with AI models potentially being able to examine complex patterns in biochemical breakdown, microbial succession, and imaging data, frequently as accurate or more accurate than conventional methods in particular research settings [2, 8, 10, 11].

Nonetheless, the road towards the integration of AI firmly and dependably into standard forensic casework is not without serious hurdles. The paramount requirement for large, heterogeneous, and standardized datasets for training and for validation is a significant hindrance [12]. Rigor of methods, above all, the use of robust external validation approaches, should be strengthened to guarantee the generalizability and validity of results [1, 2]. In addition, the "black box" character of certain complicated AI models presents legal admissibility problems, highlighting the necessity of creating explainable AI (XAI) methods appropriate for use in the forensic context [8]. Most importantly, ethical principles related to data privacy, possible bias, responsibility, and the need to ensure trust and integrity must inform the development and implementation of these potent technologies [2,4].

The potential future for AI in PMI estimation depends on their resolution by concerted, interdisciplinary action. The creation of standardized, collaborative datasets, the progress of multi-modal data fusion methods, attention to XAI, the enforcement of strict validation protocols, and perhaps the formation of field-deployable tools are essential paths forward [3, 1, 12, 13].

In summary, Artificial Intelligence promises revolution for the accuracy, objectivity, and extent of Postmortem Interval estimation. It provides a tool for unraveling the enigmatic language of postmortem alterations through combining enormous and varied datasets in a manner that exceeds human analytical capability. Although there are important challenges remaining related to data availability, validation, interpretability, and ethical deployment, current research direction is encouraging. AI stands ready not to supplant the irreplaceable experience of forensic experts but to serve as a potent synergistic instrument, enhancing their skills and eventually leading to more accurate and dependable results in the pursuit of justice. Ongoing innovation, careful scientific testing, and careful consideration of the legal and ethical environment will be crucial to making this vision a reality.

In addition to analyzing data modalities, studies are increasingly looking into the performance of various AI models for predicting PMI. Although direct comparison tends to be challenging owing to discrepancies in datasets, methods, and performance measures, some trends are apparent:

- Superiority over Conventional Techniques: Various studies indicate that ML models, specifically methods such as Artificial Neural Networks (ANNs) and Random Forests (RF), outperform conventional forensic techniques in accuracy and precision for PMI estimation, notably when working with sophisticated, multi-variable datasets [2, 10].
- Model-Specific Performance: The performance of particular model structures varies. For instance, a comparison study of ANN and RF for PMI estimation using certain features reported that the ANN universally performed better with a higher R^2 coefficient of determination and lower MAE [12]. Another study achieved high accuracy (93%) by employing a multi-organ stacking model, which integrates predictions from models trained on various tissues' data [11].
- Accuracy Measures: Scholars usually measure the performance of the model by metrics such as MAE (average difference in estimated PMI), Root Mean Squared Error (RMSE), and R^2 (variance proportion explained). Although positive outcomes are stated, low error rates for various conditions and extended PMIs consistently are still an important target [1,9,11].

AI in Postmortem Imaging and Other Applications

AI is also being used to penetrate the imaging data and other forensic evidence that pertains to PMI:

- Virtopsy and Radiomics: Postmortem computed tomography (PMCT) and MRI facilitate non-invasive imaging of internal structures and changes due to decomposition. AI, particularly CNNs, can be used to train systems to automatically interpret these high-complexity images, extracting quantitative features (radiomics) that might be linked with PMI, possibly detecting subtle alterations undetected by visual examination alone [2].
- Associated Forensic Uses: Not strictly PMI estimation but AI is also being utilized in associated autopsy and crime scene examinations, including approximating weapon types based on wound signatures, toxicological data analysis, and support for forensic identification (facial recognition, dental record comparison), showing the general incorporation of AI into forensic processes [2].

PMI estimation using AI is a fast-changing domain. As it is, existing studies clearly outline the possibility and potential advantages of using ML and DL to study varied postmortem information. Nevertheless, deriving the results of such research into scientifically established, preclinically applicable forensic tools involves overcoming substantial hurdles concerning data standardization, validation of the model, and applicability in practice.

Challenges, Limitations, and Ethical Considerations

In spite of the huge potential and high speed of development in using Artificial Intelligence for estimation of Postmortem Interval, the leap from promising research results to tested, commonly used forensic tools is impeded by some considerable challenges and limitations. In addition to that, the incorporation of AI in such a fundamental sector of the legal system requires meticulous examination of ethical consequences.

Data-Related Hurdles

The most commonly quoted barrier is money and access and quality of data to use in training and validating strong AI models [13].

• Size and Scarcity: Establishing stable ML models, particularly deep learning methods, tends to be data-intensive. Obtaining large collections of human postmortem material with well-established PMIs and extensive related data (environmental factors, subject factors, cause of death) is practically challenging owing to logistical, ethical, and practical reasons. Several existing investigations are based on comparatively limited datasets, frequently from animal models, which might restrict the transferability of their results to human casework.

• Representativeness and Diversity: Data should be diverse enough to capture the broad range of variables that affect decomposition. Models that are trained on data from one environment or population may not work well under other conditions or on individuals with different physiological profiles. Having representative data for the diverse scenarios encountered in actual forensic cases is important.

• Standardization: There are no standard protocols for data collection, sample handling, analytical procedures (e.g., particular MS platforms or sequencing strategies), and reporting of data that complicate comparison of findings between studies or meta-analyses over large datasets [1]. Setting up standardized methodologies is necessary for the generation of cumulative knowledge and cross-validation.

Methodological and Validation Challenges

In addition to data gathering, the AI-based PMI research methodologies are questioned.

• Experimental Design and Rigor: Having good experimental design with proper controls and accounting for confounding variables is essential. The intricacy of the postmortem process necessitates careful planning to separate the time effect from other factors that can affect it.

• Validation Strategies: Extensive validation is essential for any predictive or diagnostic tool that will be used forensically. Most studies use internal validation (application of the model to a subset of the same data used for training) to a large extent, which tends to overestimate the performance. External validation, application of the model to entirely independent datasets acquired under differing circumstances or by other research groups, is important to determine real-world applicability and robustness, though it is generally missing [13].

• Study Comparability: Variations in the AI algorithms selected, the methods of feature selection, the performance measures indicated, and validation methods hinder straightforward comparisons of the effectiveness of various AI approaches [1].

Model Interpretability and the "Black Box" Issue

Most strong AI models, especially intricate deep-learning structures, are "black boxes" – their internal decision-making capabilities are difficult for people to interpret [13]. This opaqueness is a serious hurdle in the judicial context, where the foundation for expert testimony and scientific evidence needs to be comprehensible and pass the test of scrutiny (e.g., under Daubert or Frye criteria in the US). Whereas a model may perform remarkably well in terms of predictive accuracy, the model's admissibility in court may be impaired if the underlying rationale is not easily communicated. Attempts in Explainable AI (XAI) try to correct this, but creating understandable but highly precise models for challenging biological data is a continuing subject of investigation.

Accounting for Variability

Though AI is superior to humans at pattern recognition, models still have to cope with the vast variability inherent in decomposition [1,3]. Bringing the impact of various environmental factors (temperature changes, humidity, insect access, burial medium) and internal individual factors (age, BMI, state of disease, medications) into predictive models in a useful way remains a challenging task [1,3]. Simplistic models can be disappointing if they fail to reproduce this variability and consequently produce bad predictions for non-standard scenarios.

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 21s, 2025
https://theaspd.com/index.php
While AI seeks to refine existing methods, existing AI-based methods are not perfect and continue to have prediction errors. Precision tends to drop as PMI increases, and meeting the high level of precision necessary for legal certainty in all timeframes and conditions is still a persistent issue [2,6]. Setting acceptable error margins for forensic uses is also a key consideration.

Ethical Considerations

The incorporation of AI in the estimation of PMI poses significant ethical considerations [2, 4]:

• AI as Enhancement, Not Substitution: It is widely argued that AI must be considered as an aid to support forensic specialists, enhancing their judgment and skills, not substitute human supervision and interpretation [4]. Excessive dependence on automated processes without rigorous review by competent personnel may result in flaws or miscarriages of justice.

• Bias and Fairness: AI systems are prone to inheriting biases from the training data. If the datasets used for training underrepresent specific populations or environmental contexts, ensuing models can perform unfairly or inaccurately for such groups or scenarios.

• Data Privacy and Security: Processing sensitive postmortem data calls for stringent privacy protection and data security protocols.

• Responsibility and Accountability: Defining responsibility when an incorrect AI-assisted PMI estimation is made calls for well-defined frameworks. Is it the developer, the data, the algorithm, or the expert interpreting it which is responsible?

• Trust and Integrity: Sustaining public and legal confidence in forensic practice calls for openness regarding the utilization of AI, its abilities, and its limitations [2].

Addressing these complex challenges – cutting across data science, forensic science, and ethics – is key to unlocking the full potential of AI in making reliable and legally admissible estimates of time since death.

Future Directions

The use of Artificial Intelligence for the estimation of Postmortem Interval is obviously an area full of promise, but it is still at a fairly early stage of development. Addressing the present challenges and harnessing the complete potential of AI in this area will be a function of collective effort in several key areas. The directions for future research and development should include the following:

1.Large, Standardized, and Diverse Dataset Development: Arguably most important is the prerequisite for advancement. Multi-center, large-scale collaborative efforts must be undertaken to create large-scale databases of high-quality human postmortem data. The datasets should contain well-determined PMIs, extensive metadata (characteristics of the individual, cause of death, minute-by-minute environmental factors), and data acquired with standardized protocols for sample collection, processing, and analysis (e.g., defined omics platform, imaging parameters). Maintaining diversity in populations, geographic settings, and environmental domains across these datasets is vital for the construction of strong and generalizable AI models [12]. Publicly available benchmark datasets would greatly speed research and enable more significant comparisons among varying AI techniques.

2.Multi-modal Data Fusion Technique Development: Since decomposition is driven by an array of factors that are represented by different data types, data fusion from multiple sources has tremendous potential to enhance the accuracy and stability of PMI. Future studies need to work on building advanced AI models that can successfully integrate data from multiple modalities – merging, for example, biochemical markers in proteomics and metabolomics with thanatomicrobiome signatures, radiomic features in PMCT imaging, and real-time environmental sensor observations [1, 3,]. These multi-modal strategies have a better chance of capturing the integrated nature of postmortem changes and giving more accurate estimates under varying conditions and timepoints.

3. Focus on Explainable AI (XAI): To connect the gap between the practice and routine forensic work, especially regarding admissibility in courts, future AI models for PMI estimation need to focus on interpretability. Investigating XAI methods specific to forensic data is essential. Creating models that not only give an accurate estimate of the PMI but also tell us why they did so (e.g., by identifying the most significant features or providing confidence scores) will be crucial for acceptance and credibility among forensic practitioners and the courts [12].

4. Emphasis on Strong Validation and Longitudinal Research: Beyond internal validation, future research has to include strong external validation with the use of independent datasets. Longitudinal research, monitoring changes in the same subject (mainly employing animal models or specially designed human taphonomy facilities) over long times and under controlled variations of the environment is required for

a deeper understanding of the dynamics of postmortem alterations and for the validation of long-term predictive power of AI models.
5.Field-Deployable Technology Development: Although laboratory-based omics and imaging technologies are strong, the end point for many purposes is to create fast, portable, and affordable technology that can be deployed at the crime scene or in a resource-poor environment. The development of miniaturized sensors, portable spectrometers, and AI algorithms tailored for on-scene analysis could create useful instruments for initial PMI estimation in the field [1].
6.Enhancing Interdisciplinary Cooperation: Advances in this area require close cooperation among forensic scientists (pathologists, anthropologists, entomologists), analytical chemists, molecular biologists, data scientists, AI researchers, statisticians, and legal experts [3]. Each brings valuable expertise to the table, and enhancing good communication and collaborative research projects will be of critical importance in cultivating solutions that are scientifically grounded, technologically possible, and legally sound.
7.Refining Specific Context Models: In place of finding a single PMI model applicable universally, future studies could aim at creating special models tailored for particular contexts, e.g., varying environmental conditions (aquatic, deserts), various tissue types, or varying PMI time frames (early, late). Model refinement for specific contexts may be more accurate within those contexts.
Through these avenues, the scientific world can methodically overcome the existing constraints and construct a solid foundation for the sound and ethical use of Artificial Intelligence in the important function of approximating the time since death, ultimately strengthening the faculties of forensic investigation.

CONCLUSION

The reliable estimation of the Postmortem Interval is still a mainstay of forensic science, but conventional techniques, despite their provenance, are flawed by the very nature of the variables in precision, objectivity, and generality, especially with the passage of time since death. The development of Artificial Intelligence has ushered in exciting new avenues, providing advanced computational techniques that can evaluate the intricate, multi-dimensional biological and chemical alterations that occur after death with a degree of sophistication hitherto unavailable [2, 3, 4,].
This review has mapped the terrain of AI's emerging function in PMI estimation. We have looked back at the roots and recognized the limitations of traditional methodologies, underlining the compelling necessity for innovation. We had ventured into the multifaceted AI paradigms, mainly Machine Learning and Deep Learning, being put to use, and had panned out the abundant data modalities – from holistic omics profiles (proteomics, metabolomics, lipidomics, transcriptomics) and thanatomicrobiome signatures to sophisticated medical imaging (Virtopsy) and physical parameters – driving these smart algorithms [1, 2]. Recent studies illustrate concrete advances, with AI models proving capable to examine complex patterns in biochemical breakdown, microbial succession, and imaging data, frequently documenting enhanced accuracy over conventional methods in certain research settings [2, 8, 10, 11].
The journey to incorporating AI solidly and securely into standard forensic casework is not entirely without substantial challenges. The urgent requirement for big, varied, and standardised training and validation datasets is a significant hindrance [12]. Methodological consistency, especially through the adoption of rigorous external validation approaches, should be strengthened to guarantee generalizability and reliability of results [1, 2]. In addition, the "black box" character of certain advanced AI models creates obstacles for legal admissibility, highlighting the need to create explainable AI (XAI) methods for application in the forensic context [8]. Most importantly, ethical principles regarding data privacy, bias possibilities, accountability, and the need to preserve trust and integrity should inform the creation and application of these technologies [2,4].
The future of AI for PMI estimation depends on overcoming these challenges in collaborative, multidisciplinary research. Standardized, communally available datasets, the exploration of multi-modal data fusion methods, attention to XAI, robust validation protocols, and perhaps the development of field-deployable tools are all key directions for advancement [13,14,15].
Data Availability: No datasets were generated during the current study.
Abbreviation:
MS: Mass spectrometry
ANNs: Artificial Neural Networks
PMI: Post-mortem interval

ML: Machine learning
DL: Deep learning
SVM: Support Vector Machines
RF: Random Forests
CNNs: Convolutional Neural Networks

Declarations

Ethics approval and consent to participate: Not applicable.

Consent for publication Not applicable.

Competing interests: Nil.

Funding: None

REFERENCES

1. Secco L, Palumbi S, Padalino P, Grosso E, Perilli M, Casonato M, Cecchetto G, Viel G. "Omics" and Postmortem Interval Estimation: A Systematic Review. Int J Mol Sci. 2025 Jan 25;26(3):1034.
2. Sacco MA, Tarzia P, Tarda L, La Russa R, Cordasco F, Aquila I. The artificial intelligence in autopsy and crime scene analysis. Clin Ter. 2024 Jul-Aug;175(Suppl 2(4)):192-195.
3. Singh J, Kumar A, Trivedi S, Pandey SK. Advancements in estimating post-mortem interval in medico-legal practice: A comprehensive review. Leg Med (Tokyo). 2025 May;74:102627.
4. Ketsekioulafis I, Filandrianos G, Katsos K, Thomas K, Spiliopoulou C, Stamou G, Sakelliadis EI. Artificial Intelligence in Forensic Sciences: A Systematic Review of Past and Current Applications and Future Perspectives. Cureus. 2024 Sep 28;16(9):e70363.
5. DiMaio VJ, DiMaio D. Forensic Pathology. 2nd ed. Boca Raton: CRC Press; 2001.
6. Garcés-Parra C, et al. Enhancing late postmortem interval prediction using bone microstructure and machine learning: a pilot study in human ribs. Biol Res. 2024 Dec 2;57(1):62. (Note: Citation details inferred from search results, requires verification for full accuracy)
7. Aljeaid R, et al. Application of Metabolomics and Machine Learning for the Estimation of Postmortem Interval Using Rat Brain Tissue. Metabolites. 2024 Nov 14;14(11):741. (Note: Citation details inferred from search results, requires verification for full accuracy)
8. Arpe J. Applied Machine Learning Predicts the Postmortem Interval Using Metabolomic Data from Porcine Brain Tissue [Master's Thesis]. Uppsala: Uppsala University; 2024.
9. Sharma R, et al. Application of artificial intelligence and machine learning algorithms in forensic science. Forensic Sci Int. 2022 Dec;341:111494.
10. Harsh, Tyagi M, Jakhar J, Viqar A. Bone proteomics in forensic investigations: advances, challenges, and methodological innovations. Int J Environ Sci. 2025;1488-94. doi:10.64252/v52v4x89.
11. Chourasia A, et al. Applying Machine Learning Techniques to Estimate Post Mortem Interval (PMI) Using Thanatomicrobiome Data. In: Proceedings of the International Conference on Recent Advancements in Machine learning, Security, and Intelligent Transportation Systems (RAMSITA-2025); 2025.
12. Lu XJ, et al. A novel method for determining postmortem interval based on multi-organ metabolomics and machine learning in rats. Forensic Sci Med Pathol. 2023 Mar;19(1):48-57.
13. Floridi L, Cowls J. A Unified Framework of Five Principles for AI in Society. Harv Data Sci Rev. 2019;1(1).
14. Malik P, et al. Development of a Machine Learning Framework for Real-Time PMI (Post-Mortem Interval) Estimation in Field Forensics. Int J Sci Res Eng Manag. 2024 Sep;8(9).
15. Harsh, Singh TK, Kishore U, Sagar A. Revolutionizing justice: how artificial intelligence is transforming autopsies and crime scene investigations. Int J Environ Sci [Internet]. 2025 Aug 4 [cited 2025 Aug 7];:1366-9. Available from: https://theaspd.com/index.php/ijes/article/view/5892