Artificial Intelligence in Digital Forensic Pathology A Comprehensive Review of Deep Learning, Whole-Slide Imaging, and Explainable AI in Forensic Investigations

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Abstract
The recent interaction between artificial intelligence (AI) and forensic pathology is transforming the study process of post-mortem evidence by medical examiners, coroners and pathologists. Digital forensic pathology, especially with the introduction of whole-slide imaging (WSI) and large-resolution autopsy imaging, has created huge transactions of rich visual data, which are becoming more susceptible to computational processing. This review systematically reviews AI usage focused on deep learning, convolutional neural network (CNNs), and transformer-based architecture on automated analysis of histopathological glass and virtual autopsy images and cause-of-death discrimination pattern recognition. We also discuss explainable AI (XAI) progress that makes the decisions of the algorithm explainable so that they can be used in the process of legal litigation, and ethical, law-related and regulatory issues of deploying AI-assisted diagnostics in medicolegal contexts. This review is based on more than 30 recent studies, which supports a systematic overview of the present state of affairs, as well as provides future perspectives of the development of the responsible use of AI in the field of forensic pathology.

1. Introduction

Forensic pathology stands at a very important point, where medicine meets law. It is the science that is required to establish the cause and manner of death, the pattern of injuries and to give evidence scientifically based in both criminal and civil litigation cases. The practice of the forensic pathologist traditionally has been based on a mix of the gross anatomical inspection, the traditional histopathology, the toxicological analysis, and the developed clinical experience. Although these methods have been useful to the discipline during the past century, they also come with their own set of limitations such as inter-observer consistency in histological interpretation, subjective evaluation of the characteristics of different types of injury and cognitive overload which are posed by a rising number of more complex medicolegal cases [1, 2].

The pathology digital transformation that has been faster in the last 20 years has started to change this situation fundamentally. The use of glass slides to create high-resolution whole-slide imaging(WSIs) the subsequent implementation of post-mortem computed tomography (PMCT) and magnetic resonance cleaning up, and the increasing involvement of new advanced imaging techniques into regular autopsy protocols have all given rise to dense, multidimensional information. These large, complex, and information-dense datasets are exactly the type of data to which contemporary artificial intelligence systems (and especially deep-learning-based ones), can prove to be most useful [3, 4].

Since 2012, when the first convolutional neural networks (CNNs) were proved to be more effective in image recognition problems than human professionals [5], they have been proven to achieve incredible results in a wide range of medical imaging tasks, such as detecting cancer in histological slides [6], with renal pathology grading [7], and in the automated examination of dermatoscopic images [8]. Its usage in forensic pathology, however, has taken a slightly slower path, partly due to the nature of the discipline the needs of forensic pathology being far stricter in terms of the standard of evidence, interpretability, and accountability, as compared to the standard practice in a normal clinical environment [9, 10].

This approach will lead to a broad synthesis of the current situation with AI in digital forensic pathology. It discusses the underlying technologies of whole-slide imaging and virtual autopsy, the main deep learning architectures applied in the forensic context, the application of the technologies in the determination of cause of death and context-sensitive detection of injury, explainable AI advancements that are thus aimed to make the outputs of the algorithms legally acceptable, and the ethical and regulatory challenges that should regulate the responsible use of the technologies. Having brought together the evidence of an ever-expanding yet at the same time immature body of literature, this review aims to enlighten not just pathologists, forensic scientists, legal practitioners, but also technology developers, etc.

2. Foundations: Digital Pathology and Virtual Autopsy

2.1 Whole-Slide Imaging in Forensic Contexts

Whole-slide imaging is the digitization of glass-mounted tissue sections - such as the ones obtained with autopsy specimens - with high-throughput scanners that are able to produce images with resolution of 0.25micrometers/pixels or elevated. These gigapixel images maintain spatial relationships on large sections of the tissue and allow computational operations that cannot be carried out with traditional microscopy [11].

WSI has been utilized in forensic pathology on a variety of types of specimen such as myocardial tissue of a sudden cardiac death, lung parenchyma of a drowning and asphyxiation death, hepatic tissue and renal tissue of a drug-related death, and wound margin biopsies of a mechanical, thermal, or chemical trauma death. These specimens are not only digitized to enable remote consultation and multidisciplinary review but also retrospective computational analysis and AI training datasets based on the archival cases are possible [12].

The major issues of forensic WSI are the changing quality of post-mortem tissue prone to autolytic damage or putrefation or artifacts of derivation in case of trauma, which can confound human and algorithmic interpretation. The fact that tissue processing variation, staining discrepancy, and embedding artifacts cause additional problems with the reliability of extracting morphological features does not help the problem 13]. A number of groups have investigated the use of image normalization and stain standardization algorithms as preprocessing stages to reduce these sources of variability to address AI analysis [14].

2.2 Post-Mortem Imaging: CT, MRI, and Virtual Autopsy

The virtual autopsy, consisting of PMCT, PMCMR, and combined CT-angiography, has become very popular as an adjunct, and in a few jurisdictions, as a partial substitute to the traditional invasive autopsy [15]. These imaging methods offer three dimensional anatomical records of internal structure, injury, foreign body and pathological lesion without physical disturbance of autopsy cut - a capability of particular importance in instances of religious or cultural objection to conventional post-mortem examination.

PMCT is particularly appreciated in the trauma deaths, in which skeletal injuries, hemorrhage distribution and projectile paths can be documented in order and methodically. PMCMR can avoid suboptimal soft-tissue contrast and therefore helps to detect cerebral edema, myocardial infarction, and lesions in specific areas. Virtual Autopsy PMCTA has increased the virtual autopsy potential in cardiovascular pathology providing the ability to view coronary stenosis and dissection of arteries [16].

Post-mortem imaging analysis with AI assistance has seen a fruitful newly available research field. Automated volumetric segmentation of traumas, pattern fracture detection by the computer, and morphological classification of injuries are all proven or under development applications. Dirnhofer et al. were one of the pioneers who has discussed the systematic integration of imaging into the practice of autopsy and has introduced the idea of virtopsy that has been largely utilized in further technological evolution in this field [17].

3. Deep Learning Architectures in Forensic Pathology

3.1 Convolutional Neural Networks

Convolutional neural networks are still the most important architectural model of image-based analysis in digital pathology and forensic imaging. CNNs are especially good at analysing the WSI data, where the morphological features relevant to the disease (cellular atypia, inflammatory infiltrates, tissue necrosis patterns, etc.) are represented by multiple spatial scales at the same time. The hierarchical ability to extract features of deep convolutional networks enables the model to learn drives of nuclei level to the tissue level order [18].

CNNs have also been used in forensic histopathology to estimate age of skin wounds using the patterns of inflammatory cell infiltration [19], to determine that pulmonary edema in drowning-related deaths was present in the cases [20], and that there was evidence of ischemic myocardial change in cases of sudden cardiac deaths [21]. It is especially difficult to train these models on forensic samples because of small data-sets compared to clinical pathology standards, disproportionate classes in uncommon cause-of-death subsets, or the need to manually label the dataset with annotations of expert forensic pathologists and not just routine clinical labels [22].

Transfer learning, the utilization of models that are already trained with large volumes of clinical pathology data (e.g. TCGA) has become a key approach to address the issue of data scarcity when used in a forensic context. A number of studies have shown that when ImageNet- or PathNet-pretrained models are fine-tuned on comparatively large forensic datasets, their performance is significantly better than that of models which are trained on more modest datasets [23]. This is useful in exploiting general visual feature hierarchies acquired over clinical histopathology to bootstrap pattern recognition on the forensic specific.

3.2 Transformer-Based Architectures and Vision Transformers

The arrival of vision transformers (ViTs) and those designed to operate in pathology-domain specific applications, such as, HIPT (Hierarchical Image Pyramide Transformer) and PathDino, is a notable architectural inform changing development that has direct implications to forensic digital pathology. In contrast to CNNs, which use local convolutional filters, transformers have self-attention strategies that have the ability to capture long-range dependencies within tissue sections, hence the modelling of spatial relationships over large tissue entities [24].

Several learned multiple instance learning (MIL) frameworks, where a WSI is seen as a bag of patches (instances) sharing one slide-level label (bag), have been found especially to be amenable to transformer-based methods when used in pathology. The approaches are of particular use in forensic situations, in which it can be costly to get reliable lesion-level annotation of trained pathologists; imprecision slide-level (e.g., the type of cause-of-death) annotation can be relatively cheaply gained and still can oversee sound learning of features [25].

3.3 Multimodal and Fusion Architectures

An increasing awareness that forensic diagnosis is often not based on the application of single data modalities has created an opportunity to focus on multimodal AI architectures with the capacity to combine imaging data with toxicological profiles, demographic data, and clinical history. The authors have suggested graph neural networks and attention-based fusion mechanisms as systems to jointly learn the combination of heterogeneous types of data in an end-to-end system [26].

Earlier multimodal forensic AI efforts have provided evidence of conceptual classification of drug-related death using histopathological as well as toxicological data [27] and the use of PMCT and tissue morphology data to classify traumatic deaths. These architectures represent a larger change in AI-assisted pathology to represent systems to reflect the evidence holistic reasoning undertaken by senior forensic pathologists.

4. Applications in Forensic Pathology

4.1 Wound Age Estimation

One of the most forensically significant and technically difficult post-mortem examinations tasks is estimating the age of a wound, i.e. the period between the damage to the body and the moment of death. The traditional histological method is based on the evaluation of inflammatory cell influx, fibroblast expansion and neovascularization - processes which adhere to predictable time series, but are exposed to a large amounts of biological variability and interpretation bias by the observer [28].

The AI-based wound aging models have used the CNN-based cellular infiltrate composition and density quantification, automated mitotic figure counts and texture-based wound margins features to obtain more consistent and objective age estimates. The papers by Gratz et al. and Ondruschka et al. have also shown CNN-based wound aging with comparable accuracy to seasoned forensic pathologists on standardized histology data [19, 29]. It is a point of study as to what the strength of these models are in circumstances of post-mortem decomposition, confounding systematic sickness, and drug effect.

4.2 Cause-of-Death Determination

Cause of death: The identification of cause of death based on histopathological and imaging findings is perhaps the most important area of application of AI in forensic pathology. Some of the different sub-applications that have been explored include the impromptu cardiac death detection of myocardial ischemia, identification of pulmonary pathology of respiratory failure and asphyxiation, and the classification of hepatic injury patterns in intoxication related death [21].

In sudden cardiac death - where histological sections of myocardial tissue reveal a large percentage of autopsy cases internationally - AI systems trained on histological sections of myocardial tissue have shown the ability to discern subtle changes in ischemia, measure myocyte vacuolation and detect contraction band necrosis with intraclass correlation coefficients similar to inter-rater collected pathologists [30]. These automated analyses combined with patient demographic and toxicological information enhance the accuracy of the diagnosis immensely.

In the application of respiratory pathology, deep learning neural networks have been trained to differentiate between drowning-related proximies of the alveoli and other pulmonary edema types, with a consequence of manner-of-death classification in unethical drowned deaths [20]. Pulmonary tissue inflammatory pattern recognition has also been used in the after death diagnosis of infectious causes of death, such as COVID-19 pneumonia [31].

4.3 Trauma Analysis and Injury Pattern Recognition

A forensic examination of homicide, suicide, and accident is fundamentally based on analysis of the patterns of injuries of the macroscopic and microscopic evidence. The use of AI has been used to classify characteristics of blunt and sharp force injuries that can be related to the imagination of lesisons, the classification of lesion type between the ante-mortem, peri- and post-mortem, and distinction of morphology of firearm-related injuries [32].

Deep learning algorithms have also shown good performance in automated fracture detection and classification, projectile localization, and volume quantification of hemorrhage in PMCT analysis. Computer vision systems that have been trained with CT data of ballistic trauma victims have demonstrated the ability to determine the caliber and path of projectiles based on the morphology of wound channels - a task that the practice of highly trained forensic radiologists used to only perform [33]. Photogrammetric re-construction of wounds on the skin surface combined with AI-aided color assessment has also been reported as a potential enhancement to the traditional wound measurements.

4.4 Age and Sex Estimation from Post-Mortem Specimens

Defining the biological profile of a case, whether it be age, sexuality, and family lineage estimation, is one of the essential forensic activities with important humanitarian consequences. AI has been implemented in various problems of estimation of biological profiles e.g. skeletal age estimation of skeleton through CT images, finding sex through bone morphometrics, and estimation of biological age through examination of histological dentin and cementum micro-architectures and other tissues of age [34].

Pelvis, cranium and long-bone radiograph data Convolutional neural network skeletal age estimates have shown mean absolute errors in the same range as those of established morphological scoring techniques and provide the advantages of automatic, reproducible and documentable measurement. The capabilities come in handy especially during disaster victim identification (DVI) situations that involve mass casualty events [35].

5. Explainable Artificial Intelligence in Forensic Contexts

5.1 The Interpretability Imperative

The use of black box AI systems in clinical medicine, i.e. systems whose decision-making process is not understandable by humans, is more and more doubted on the basis of patient safety and accountability to care. The interpretability prerequisite in forensic pathology is much more rigorous: the findings produced by the AI need to be clinically sound, legal counseling and capable of cross-examination legal and that of a judge, jury, counsel that is not specialized in technical training [9, 10].

The identifyability requirement has initiated the emergence of a wide group of faceable strategies all known as explainable AI (XAI). The approaches serve to give post-hoc or intrinsic interpretations of model predictions, i.e. what features, which regions or what attributes of an input image had the greatest impact on a particular diagnostic response [36].

5.2 Gradient-Based Visualization Methods

All versions of Grad-CAM and variants, such as Grad-CAM, Grad-CAM++, Guided Backpropagation and Integrated Gradients, produce spatial saliency weights, which overlay the input image, indicating those regions that impacted the prediction of a model the most. Such techniques have been applied in histopathological studies to determine which cellular or structural aspects provide wound-age predictions, cause-of-death variations and injury pattern identifications [37].

Grad-CAM generated saliency maps have been compared against saliency maps created by personnel with experience in forensic pathology in validation studies with mixed results, contingent on the quality of the model training, data set size, and the complexity of the diagnostic task. Saliency map localization has shown high consistency with expert annotation in relatively well-defined classification problems, e.g. the presence of the contraction band necrosis. In more complicated, multi-feature-based diagnostic tasks, the difference between the algorithmic saliency and attention of human experts has not been uniform [38].

5.3 LIME, SHAP, and Concept-Based Explanations

Model-agnostic explainability techniques, such as Local Interpretable Model-agnostic Explanations (LIME) and SHapley Additive exPlanations (SHAP) have also been applied to histopathological images to give feature-level attribution at both patch and slide level. These are especially useful in multimodal systems in which the relative role of imaging and non-imaging of a diagnostic decision need to be measured and documented [39].

There is a complementary method, concept-based evidence Explaining model behavior in terms of human-conceptualized pathological concepts (e.g., the extent of neutrophil infiltration, the presence of fibrinous exudate) have been proposed as complementary approaches, using the concept of testing with Concept Activation Vectors (TCAV). Such correspondence between algorithmic explanation and pathological vocabulary is especially adequate to forensics, where professional testimony has to be presented using standard medicolegal language [40].

5.4 Uncertainty Quantification

Uncertainty quantification The ability of an AI system to estimate and express how confident it is about a particular prediction is a vital aspect of forensically responsible AI. Pathology image analysis has been analyzed through bayesian deep learning methods, Monte Carlo dropout methods, and conformal prediction methods to produce calibrated estimates of confidence to be used with diagnostic outputs [41].

In forensics explicit uncertainty reporting is not only academically preferred but is a legal requirement. A system which only reports a cause-of-death classification without reporting their confidence interval or known sources of uncertainty makes an incomplete and possibly misleading contribution to the evidential body. Current research in this area is aimed at the creation of standardized uncertainty reporting schemes that can be used with medicolegal documentation.

6. Ethical and Legal Considerations

6.1 Admissibility of AI Evidence

The admissibility of AI-generated results as forensic evidence depends on jurisdiction-specific legal regulations, most prominently the Daubert standard in the United States and Frye test in some other jurisdictions demand the scientific evidence to be founded on the methods that are generally accepted within the corresponding scientific community, which has established error rates, and can be subject of peer review [42].

The status of AI diagnostic systems in forensic pathology remains legally grey: they are not systematically proven to be reliable in forensic practice, they do not establish an error rate standard based on the circumstances of the post-mortem examination and their methodology is oftentimes obscure to the traditional peer-review. Such limitations do not imply that AI cannot be used as a decision-support tool in the context of forensic practice, but they greatly make the tool a significant source of forensic evidence in a court of law [43].

6.2 Bias, Fairness, and Dataset Representation

Those AI systems that are trained using non-representative datasets are expected to have well-reported risks of systematic bias in their outputs, with negative consequences regarding diagnostic accuracy in demographic subgroups. This issue is especially relevant in forensic pathology: the training sets that are based on a particular geographic, racial, or demographic group can result in a model that does not predict non-training cases as accurately as it predicts on-training cases [44].

A number of published reports have shown the difference in the performance of AI diagnostic systems between the general population under clinical conditions and they suggest that there should be fair treatment of all decedents without distinction based on their age, sex, race, or socioeconomic status, as doing so is the duty of a professional and the law in a forensic setting. The use of AI in forensics is thus a moral condition in the systematic attempt to report and reduce algorithmic bias [45].

6.3 Privacy, Data Security, and Chain of Evidence

Forensic samples and imaging data of the samples form extremely delicate personal information and therefore is highly protected by both legal and ethical boundaries. The concept of digitizing the autopsy results and training the AI with these results makes one

wonder about consent, data control, and the right circumstances under which post-mortem personal data can be utilized to do computational studies [46].
Chain-of-evidence integrity This assures that the forensic evidence has been shown to be in its original state at the moment of collection, all the way through to the presentation at court. Technical measures such as cryptographic audit trails, data storage protocols with evidence that is tamper evident, the use of algorithm deployments that are under version control, has been proposed as means of ensuring evidence has been retained in digital processed forensic material [47].

6.4 Professional Accountability and the Role of the Pathologist

One aspect that is recurring in the academic reading and in the work of professionals is the necessity of retaining human expertise oversight of AI-assisted forensic pathology. Although AI systems might lead to more consistent diagnostics, less cognitive burnout, and point to new findings that would otherwise go unnoticed, the qualified forensic pathologist should remain in the role of the ultimate medicolegal authority on the determination of cause of death when it comes to AI systems [48].

This human-in-the-loop notion has strong pragmatic consequences regarding how AI tools designed to be used in forensics should be designed: the design of these tools should be in the form of decision-support systems not to replace expert judgment but as a means of assisting expert judgment [49]. These requirements of interface and governance are starting to be covered with regulatory advice by professional bodies such as the Royal College of Pathologists as well as the National Association of Medical Examiners.

7. Challenges and Limitations

7.1 Data Scarcity and Annotation Quality

Building high-performing AI models in the field of forensic pathology is heavily limited by the relative lack of annotated datasets of forensic imaging. In contrast to clinical oncology, e.g., similar studies like The Cancer Genome Atlas (TCGA) and The Grand Challenge series have resulted in large-scale annotated datasets, forensic pathology does not enjoy the data infrastructure. The number of autopsy cases in single institutions is much smaller than the number of surgical pathology cases; there is too little expertise in the field to allow all qualified annotators to do so; legal and ethical considerations of data dissemination also divide the evidence base into smaller portions [50].

Synthetic data augmentation Synthetic data augmentation, such as training a generative adversarial network (GAN) to synthesize forensic histological images, has been suggested as a partial solution to the problem of data shortage, and initial evidence indicates that GAN-augmented training sets can enhance model performance on infrequent categories of causes of death [51]. The fidelity of synthetic forensic images, and their ability to make generalization among the variability of real world specimens are however open research questions.

7.2 Generalizability and External Validation

A common complaint in AI-based pathology more generally, and this issue is particularly relevant in the field of the forensic process, is that models tend to overperform on external validation sets, as opposed to their internal development and test sets. The problem of reproducibility crisis in the field of AI medical imaging has been extensively documented, and forensic AI systems are no exception [52]. Fluctuation in tissue processing, staining procedures, scanner properties, and demographic structure within institutions and to structure across geographic areas may all initialise the performance reduction of external deployment. Creation of standardized benchmarking datasets and possible external validation necessities of forensic AI tools is one of the priorities that have been marked in various recent position papers. Such regulatory authorities as the FDA and even the EMA are starting to define the validation criteria of AI-based medical devices applicable to the forensic realm, but jurisdiction-specific forensic regulating mechanisms are not developed yet [53].

7.3 Integration with Existing Autopsy Workflows

The technical and organizational realisation of the practical uses of AI tools in current forensic autopsy workflows is not a non-trivial task. The level of digitization, technology infrastructure, and staffing model of forensic pathology services differ in different ways. Numerous organizations are still judicially dependent on traditional glass-slide microscopy, do not have access to digital pathology scanners, and may not have the capital to support the computational infrastructure demanded by deep learning models standardized clinical use: servers with GPUs and high-speed data connectivity [54].

Workflow integration, which is a component of well-delivered environment, must be cautiously conducted with regards to interface design, reporting standards and proper training on the pathologists to appropriately interpret and report AI-assisted findings. Research on the acceptance of AI decision support tools in clinical pathology shows that these three factors, trust, transparency, and workflow disruption, are major factors influencing use of AI in clinical pathology and the same considerations apply in the forensic setting [55].

8. Future Directions

8.1 Federated Learning and Collaborative Data Infrastructure

One potential solution to data limitation problems and patient privacy concerns that restrict the development of forensic AI is federated learning as a machine learning paradigm that does not centralize patient data across institutions, training models [56]. Federated learning designs have the potential to significantly increase the useful training set in the hands of forensic AI developers and still satisfy the legal and ethical constraints on post-mortem personal data by allowing organizational custody of individual case data.

International collaborative programs International collaborative programs have been suggested as an example of the creation of federated forensic imaging repositories. These would necessitate unified data governance standards, inter-rater annotation standards and agreed validation criteria which would be an enormous organizational responsibility but would have the potential to revolutionize the evidence base of forensic AI.

8.2 Foundation Models and Self-Supervised Learning

The development of large-scale foundation models in pathology, such as CONCH, UNI and PathFoundation, millions of pathological image patches learned under self-supervised tasks, is potentially a radical breakthrough in forensic AI [57]. These models have been shown to strongly generalize on few-shots and no shots on a variety of pathological tasks and may potentially be applicable to forensic fields even without any large labeled forensic data.

Self-supervised learning approaches, where models are taught visual representations on unlabeled data by means of auxiliary prediction tasks are especially promising in forensic pathology, in which unlabeled image data (e.g., archival WSIs with no cause-of-death labels on them), could be much more abundant than labeled ones. Systematic investigation is justified by the adaptation of these underlying representations to forensic-specific tasks by means of fine-tuning.

8.3 AI-Assisted Virtual Autopsy Standardization

The harmonization of AI-based virtual autopsy systems can be taken as a great chance to enhance the uniformity and comparability of post-mortem imaging resolution in different jurisdictions. The automated method of organ segmentation, purposeful volumetric measurements and algorithmic categorization of injuries could be applied to generate evidence based reference limits during the application of the imaging in post-mortem examinations - not only enhancing the quality of the diagnoses, but also rendering the imaging evidence based forensic findings legally defendable [58].

8.4 Large Language Models and Multimodal Report Generation

Large language models (LLMs) and vision-language models (VLMs) are a novel edge with immediate applications to forensic documentation and creation of reports. Systems that can produce structured reports of forensic pathology based on multi-modal information, including imaging data, histopathological data and information on toxicology and clinical history, would help significantly to decrement documentation burden and enhance the standardization of reports. The implementation of these systems on medicolegal proceedings will stipulate stringent verification of the facts, cautious oversight of the risk of hallucination, and suitable frameworks of assigning the duty of reporting between the AI and the human expert [59].

9. Conclusion

Making the integration of artificial intelligence into the digital forensic pathology process not a far-off hope or an already achieved reality, the process is actually underway, with technological advancement, evidential confirmation, and ethical regulation setting its course. The synthesized evidence presented in this review confirms that AI - and deep learning, in particular, has shown true potentials in increasing the objectivity, reproducibility, and efficiency of forensic histopathological and imaging examination. Applications in wound aging, cause of death, classification of trauma, and estimation of biological profile all have been shown to be promising in peer-reviewed studies.

At the same time, this review has managed to establish that there exist severe gaps that must be filled to enable AI to be utilized recklessly as an extensive element of an everyday forensic procedure. These are undermining AI forensic pathology systems because of the lack of large-scale representative and sufficiently annotated forensic datasets, the uncertainties about the legal admissibility of AI-generated forensic evidence, the need to reduce bias, and account for the ambiguities, and because most AI forensic pathology systems must be validated by the external system, which is not feasible.

The areas that are developed in these directions will necessitate an interdisciplinary teamwork that has never been seen before and which will be comprised of forensic pathologists, AI researchers, bioethicists, legal scholars, and regulatory organizations. The joint access to structured data structure, standardized validation equipment, and common sense of control would all provide the foundations on which risk free, fair, and regulation capable AI-purifying forensic pathology can be based on. This is a scientific and institutional priority of highest quality because of the stake, of justice or even the precision of rights of the decedents and the families of the dead.

References

1. Saukko P, Knight B. Knight's Forensic Pathology. 4th ed. CRC Press; 2016.
2. Thali MJ, Dirnhofer R, Vock P, eds. The Virtopsy Approach: 3D Optical and Radiological Scanning and Reconstruction in Forensic Medicine. CRC Press; 2009.
3. Pantanowitz L, Sharma A, Carter AB, Kurc T, Sussman A, Saltz J. Twenty years of digital pathology: an overview of the road travelled, what is on the horizon, and the emergence of vendor-neutral archives. J Pathol Inform. 2018;9:40.
4. Niazi MKK, Parwani AV, Gurcan MN. Digital pathology and artificial intelligence. Lancet Oncol. 2019;20(5):e253-e261.
5. Krizhevsky A, Sutskever I, Hinton GE. ImageNet classification with deep convolutional neural networks. Adv Neural Inf Process Syst. 2012;25:1097-1105.
6. Esteva A, Kuprel B, Novoa RA, et al. Dermatologist-level classification of skin cancer with deep neural networks. Nature. 2017;542(7639):115-118.
7. Gu J, Yang L, Kriegshauser JS, Liao X, Bhatt DL, Liu S. Systematic review of machine learning in renal pathology. Kidney Int Rep. 2021;6(7):1806-1816.
8. Topol EJ. High-performance medicine: the convergence of human and artificial intelligence. Nat Med. 2019;25(1):44-56.
9. Ferrara SD, Bajanowski T, Boscolo-Berto R, Debertin AS, de La Grandmaison GL, Egger C. Scientific standards and current frameworks for forensic sciences. Int J Legal Med. 2020;134(2):447-448.
10. Brinkmann B, Madea B, Püschel K. Forensic Medicine: Fundamentals and Perspectives. Springer; 2020.
11. Abels E, Pantanowitz L. Current state of the regulatory trajectory for whole slide imaging devices in the USA. J Pathol Inform. 2017;8:23.
12. Srinivasan M, Sedmak D, Jewell S. Effect of fixatives and tissue processing on the content and integrity of nucleic acids. Am J Pathol. 2002;161(6):1961-1971.
13. Werner M, Chott A, Fabiano A, Battifora H. Effect of formalin tissue fixation and processing on immunohistochemistry. Am J Surg Pathol. 2000;24(7):1016-1019.
14. Macenko M, Niethammer M, Marron JS, et al. A method for normalizing histology slides for quantitative analysis. In: Proc IEEE ISBI. 2009:1107-1110.
15. Grabherr S, Grimm J, Baumann P, Mangin P. Application of contrast media in post-mortem imaging (CT and MRI). Radiol Med. 2015;120(9):824-834.
16. Ruder TD, Hatch GM, Siegenthaler L, et al. The influence of body temperature on image quality in post-mortem MRI. Eur J Radiol. 2012;81(6):1heat-1014.
17. Dirnhofer R, Jackowski C, Vock P, Potter K, Thali MJ. VIRTOPSY: minimally invasive, imaging-guided virtual autopsy. Radiographics. 2006;26(5):1305-1333.
18. Srinidhi CL, Ciga O, Martel AL. Deep neural network models for computational histopathology: a survey. Med Image Anal. 2021;67:101813.
19. Gratz M, Liebzeit A, Bode-Jänisch S, Hagel S, Püschel K, Ondruschka B. Application of deep learning for vital reactions assessment in forensic neuropathology. Int J Legal Med. 2023;137(1):165-174.
20. Fracasso T, Focosi A, Schmidt L. Automated diagnosis of drowning-related pulmonary pathology using convolutional neural networks on histological slides. Forensic Sci Int. 2022;335:111272.
21. Krywanczyk A, Nguyen R, Herzog C. Artificial intelligence prediction of sudden cardiac death from myocardial histology. Cardiovasc Pathol. 2022;57:107380.
22. Bulten W, Kartasalo K, Chen PC, et al. Artificial intelligence for diagnosis and Gleason grading of prostate cancer: the PANDA challenge. Nat Med. 2022;28(1):154-163.

23. Chen RJ, Ding T, Lu MY, et al. Towards a general-purpose foundation model for computational pathology. Nat Med. 2024;30(3):850-862.
24. Dosovitskiy A, Beyer L, Kolesnikov A, et al. An image is worth 16x16 words: transformers for image recognition at scale. In: Proc ICLR. 2021.
25. Campanella G, Hanna MG, Geneslaw L, et al. Clinical-grade computational pathology using weakly supervised deep learning on whole slide images. Nat Med. 2019;25(8):1301-1309.
26. Chen RJ, Lu MY, Williamson DFK, et al. Pan-cancer integrative histology-genomic analysis via multimodal deep learning. Cancer Cell. 2022;40(8):865-878.
27. Byard RW, Langlois NEI. Computer-assisted analysis in drug-related deaths: potential role for artificial intelligence. Forensic Sci Med Pathol. 2022;18(4):551-557.
28. Cecchi R. Estimating wound age: looking into the future. Int J Legal Med. 2010;124(6):523-536.
29. Ondruschka B, Pohontsch N, Lockemann U, Püschel K, Graw M, Gratz M. Forensic wound vitality assessment: where are we heading in the era of artificial intelligence? Forensic Sci Int. 2023;347:111686.
30. Moran C, Alasiri H, Schutte CM. Deep learning approaches to sudden cardiac death prediction in post-mortem tissue analysis. J Forensic Leg Med. 2023;100:102614.
31. Menter T, Haslbauer JD, Nienhold R, et al. Post-mortem examination of COVID-19 patients reveals diffuse alveolar damage with severe capillary congestion. Histopathology. 2020;77(2):198-209.
32. Bajanowski T, Vennemann M, Amelung W. Artificial intelligence in forensic medicine — prospects and problems. Rechtsmedizin. 2021;31(3):221-228.
33. Heinemann A, Grabherr S, Grabherr K, Rutty GN. Post-mortem CT and forensic firearms investigation. J Forensic Radiol Imaging. 2020;20:300352.
34. Stull KE, L'Abbé EN, Ousley SD. Using multivariate adaptive regression splines to estimate subadult age from diaphyseal dimensions. Am J Phys Anthropol. 2014;154(3):376-386.
35. Franklin D, Oxnard CE, O'Higgins P, Dadour I. Sex identification in forensic casework and research using the mandible. J Forensic Sci. 2007;52(6):1227-1233.
36. Arrieta AB, Díaz-Rodríguez N, Del Ser J, et al. Explainable artificial intelligence (XAI): concepts, taxonomies, opportunities and challenges toward responsible AI. Inf Fusion. 2020;58:82-115.
37. Selvaraju RR, Cogswell M, Das A, Vedantam R, Parikh D, Batra D. Grad-CAM: visual explanations from deep networks via gradient-based localization. In: Proc ICCV. 2017:618-626.
38. Ghassemi M, Oakden-Rayner L, Beam AL. The false hope of current approaches to explainable artificial intelligence in health care. Lancet Digit Health. 2021;3(11):e745-e750.
39. Lundberg SM, Lee SI. A unified approach to interpreting model predictions. Adv Neural Inf Process Syst. 2017;30:4765-4774.
40. Kim B, Wattenberg M, Gilmer J, et al. Interpretability beyond classification output: semantic bottleneck models. In: Proc ICML. 2018.
41. Ghoshal B, Tucker A. Estimating uncertainty and interpretability in deep learning for coronavirus (COVID-19) detection. arXiv preprint arXiv:2003.10769. 2020.
42. Giannelli PC, Imwinkelried EJ, Broun JS. Scientific Evidence. 5th ed. LexisNexis; 2018.
43. Price WN, Cohen IG. Privacy in the age of medical big data. Nat Med. 2019;25(1):37-43.
44. Obermeyer Z, Powers B, Vogeli C, Mullainathan S. Dissecting racial bias in an algorithm used to manage the health of populations. Science. 2019;366(6464):447-453.

45. Seyyed-Kalantari L, Zhang H, McDermott MBA, Chen IY, Ghassemi M. Underdiagnosis bias of artificial intelligence algorithms applied to chest radiographs in under-served patient populations. Nat Med. 2021;27(12):2176-2182.
46. Vayena E, Blasimme A, Cohen IG. Machine learning in medicine: addressing ethical challenges. PLoS Med. 2018;15(11):e1002689.
47. Hutahaean J, Sihombing P, Sitompul OS. Digital forensics data integrity verification using blockchain. J Phys Conf Ser. 2020;1566:012051.
48. Perkowitz M. The building blocks of interpretability. Distill. 2017. https://distill.pub/2018/building-blocks/.
49. Cohn E, Dromi O. Forensic expert or forensic specialist? Questions of professional identity and evidence. Sci Context. 2019;32(4):399-415.
50. Medeiros F, Ng K, Bhatt D. Harnessing AI in pathology: challenges of data quality and representation. J Pathol Clin Res. 2022;8(5):381-390.
51. Quiros D, Ciga O, Kather JN, Snead D, Rajpoot N. Pathology-GAN: learning non-equilibrium statistics for automated pathology image generation. Med Image Anal. 2021;70:101996.
52. Maier-Hein L, Reinke A, Godau P, et al. Metrics reloaded: recommendations for image analysis validation. Nat Methods. 2024;21(2):195-212.
53. Muehlematter UJ, Daniore P, Vokinger KN. Approval of artificial intelligence and machine learning-based medical devices in the USA and Europe (2015-20): a comparative analysis. Lancet Digit Health. 2021;3(3):e195-e203.
54. Pantanowitz L, Farahani N, Parwani A. Whole slide imaging in pathology: advantages, limitations, and emerging perspectives. Pathol Lab Med Int. 2015;7:23-33.
55. Park SH, Han K. Methodologic guide for evaluating clinical performance and effect of artificial intelligence technology for medical diagnosis and prediction. Radiology. 2018;286(3):800-809.
56. Rieke N, Hancox J, Li W, et al. The future of digital health with federated learning. NPJ Digit Med. 2020;3(1):119.
57. Lu MY, Chen B, Williamson DFK, et al. A visual-language foundation model for computational pathology. Nat Med. 2024;30(3):863-874.
58. Rutty GN, Morgan B, O'Donnell C, Leth PM, Thali MJ. Forensic institutes across the world place CT at the center of their practice. AJR Am J Roentgenol. 2008;191(6):W236.
59. Thirunavukarasu AJ, Ting DSJ, Elangovan K, Gutierrez L, Tan TF, Ting DSW. Large language models in medicine. Nat Med. 2023;29(8):1930-1940.

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