

Estimating Bloodstain Age from Colorimetric Parameters Using Neural Network Regression

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Abstract

The estimation of the age of the bloodstains represents a critical issue in forensic science, as it provides valuable temporal information for crime scene reconstruction. Previous studies have explored colorimetric features of blood degradation and applied statistical or kernel-based machine learning models to predict bloodstain age. In this work, we propose the application of a neural network regression model to analyze colorimetric parameters extracted from bloodstains monitored over a period of 24 hours. As shown by experimental results, the proposed approach reports reduced error compared to the state-of-the-art regression methods. Our findings demonstrate the potential of neural networks to capture nonlinear relationships in blood color degradation, offering a promising and innovative framework for objective bloodstain age estimation.

Keywords

Bloodstain Age Estimation, Neural Networks, Regression, Forensic Science

1. Introduction

In forensic investigations, a wide range of traces can be collected at crime scenes, including footprints, fingerprints, hair, and bloodstains. Among these, bloodstains are a particularly valuable source of information. Their examination can aid crime scene reconstruction by analyzing their distribution and morphology [1][2], tracing their point of origin to locate voluntary or accidental blows [3][4], and estimating bleeding time to approximate when the criminal event occurred [5].

The last point, the estimation of bloodstain age, is one of the central challenges in forensic science. For this reason, over the years, several techniques have been employed for this purpose. In particular, chromatography [6] enables the separation and identification of individual blood components, providing detailed information on chemical changes over time. However, it requires complex sample preparation, expensive instrumentation, and is generally destructive, making it less suitable for on-site forensic applications. Spectroscopy methods [7] [8] allow monitoring of molecular and structural transformations, and some approaches (e.g., Raman spectroscopy) can perform single-point measurements with minimal sample preparation. Despite these strengths, spectroscopic techniques often demand costly equipment and specialized expertise, and their results can be sensitive to environmental conditions. Considering these aspects, our work focuses on colorimetry as the primary method for bloodstain age estimation [9], due to its combination of speed, simplicity, portability, non-destructive nature, which make it particularly suitable for practical forensic applications.

In recent years, colorimetry has been increasingly applied for bloodstain age estimation, exploiting the time-dependent changes in the visible color of blood. Several studies have demonstrated that specific colorimetric parameters, such as red, green, and blue (RGB) components or derived indices, correlate with blood degradation over time. These methods, often combined with statistical or traditional machine learning models, have shown promising results. In particular, in [10], a multiple linear regression model, a multiple quadratic regression, a support-vector machine for regression with Gaussian kernel, and a

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SVM with polynomial kernel are used with promising results. Instead, in [11], random forest regression is used. However, the predictive accuracy of current colorimetric approaches could be limited when dealing with the nonlinear and complex nature of blood color transformations in real-world scenarios.

Starting from this state of the art, this paper explores an alternative machine learning approach based on neural network regression for estimating bloodstain age. Neural networks are a particularly promising solution, as they can effectively capture subtle and nonlinear relationships within data, such as colorimetric features. In this study, the neural network architecture and its hyper-parameters were carefully tuned to optimize predictive performance. Experiments were conducted on a dataset of colorimetric parameters extracted from bloodstains monitored over a 24-hour period. The results demonstrate that the proposed approach outperforms existing methods in terms of standard regression evaluation metrics, highlighting its potential as a reliable tool for forensic bloodstain age estimation.

2. Data and Methodology

This section is devoted to describing materials and methods used in this work.

2.1. Dataset

This study involves a dataset containing colorimetric features reported in [10]. In detail, the dataset was created by applying a colometry study on a set of generated bloodstains. For the preparation of bloodstains, untreated whole blood was collected from healthy volunteers aged between 25 and 35 years. Immediately after collection, the blood was handled carefully to preserve its natural composition, including plasma, cells, and hemoglobin. Blood droplets were deposited onto clean, inert surfaces under controlled laboratory conditions to simulate typical forensic scenarios. The samples were allowed to age at room temperature (approximately 25°C) under standard humidity and lighting conditions. Care was taken to minimize external contamination and to ensure reproducibility across all samples. The resulting bloodstains were then monitored over time to extract colorimetric parameters for subsequent analysis. The colorimetric properties of the bloodstains for age estimation were measured using a spectrophotometer (3NH, NS800, SHENZHEN TreeNH TECHNOLOGY CO., LTD, SHENZHEN, P.R. China) with an 8 mm spot size. Prior to measurements, the lighting conditions, color evaluation settings, and calculation procedures were configured, allowing the device to directly provide the results as CIELAB/CIELCh parameters. During a 24-hour period, measurements were taken hourly, with the exception of the interval between the thirteenth and twentieth hours. Each bloodstain was measured five times, and the average value of these measurements was used for all subsequent analyses. Following the scanning process, the spectrophotometer provided color information in two color spaces: CIELAB and CIELCh. In the CIELAB system, the L^* coordinate indicates lightness, ranging from 0 (black) to 100 (white). The a^* coordinate represents the red–green axis, with negative values corresponding to green and positive values to red. The b^* coordinate describes the blue–yellow axis, where negative values indicate blue and positive values indicate yellow. The CIELCh space is derived from CIELAB and uses polar coordinates instead of Cartesian ones: C^* represents chroma, indicating relative saturation, while h^* denotes hue angle, corresponding to the angle of the color in the CIELAB color wheel. All five parameters of the CIELAB and CIELCh color spaces (L^* , a^* , b^* , C^* and h^*) for 136 instances were used to train and test the proposed machine learning model and obtain bloodstain age estimation.

2.2. Methodology

Our study investigates the application of Neural Network Regression (NNR) to estimate the bloodstain age for forensic goals. The workflow of the study is reported in Fig. 1. Precisely, raw data have been split in training and test parts. Validation part has been extracted from training part for a tuning procedure. The optimized NN model have been used on the test part in order to analyse and discuss its performance. Hereafter, more details about our methodology are given.

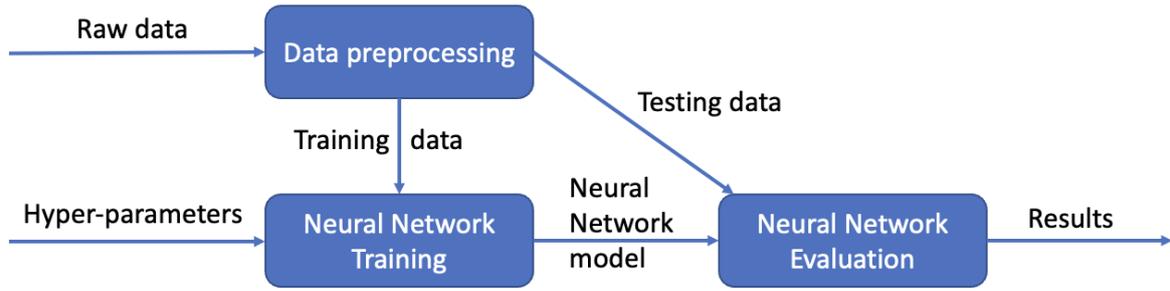


Figure 1: Workflow of our proposal

2.2.1. Data preprocessing

The dataset was split into training and test sets following a typical 80–20% ratio. From the training portion, 10% of the samples were further set aside as validation data. Given the limited dataset size, no feature selection or extraction techniques were applied. At this stage, a correlation matrix (see Fig. 2) was analyzed to explore the degree of linear dependence between the features and the target variable. This preliminary assessment not only provides insights into the most influential predictors but also highlights the potential presence of more complex, non-linear interactions. Such evidence further supports the suitability of NNR, which is capable of modeling both linear and non-linear relationships.

2.2.2. Neural Network Training

Our approach consists of using a typical NN used for solving regression problem. Briefly, NNs are characterized by an architecture organized in layers: an input layer that receives the predictors, one or

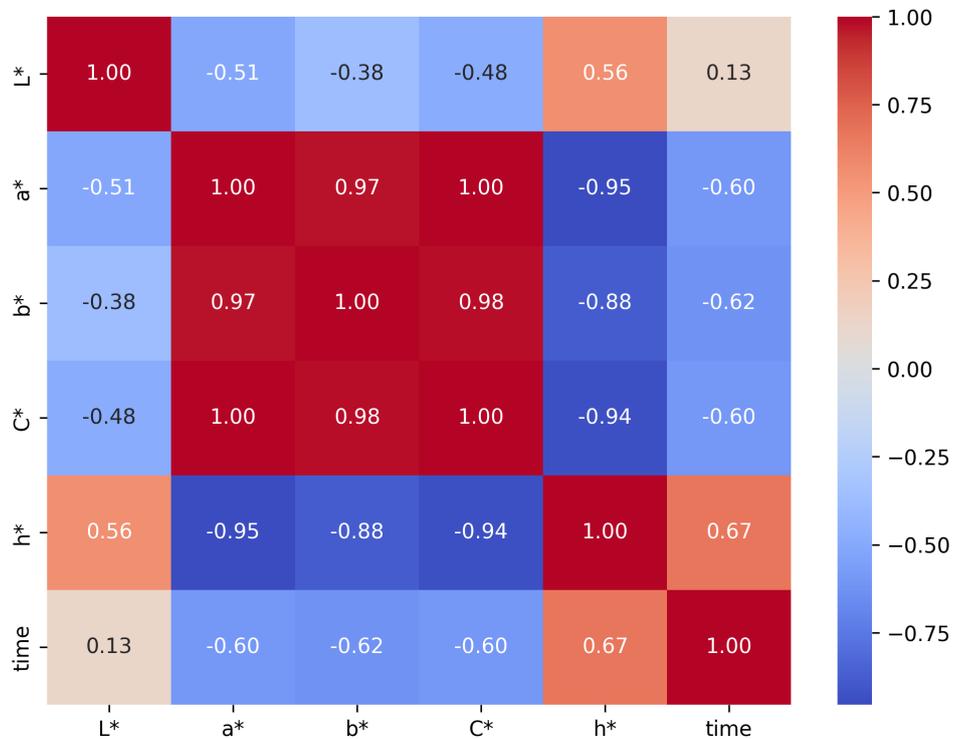


Figure 2: Correlation matrix

more hidden layers that transform the information through interconnected neurons, and an output layer that produces the final prediction. Each neuron computes a weighted sum of its inputs followed by a non-linear activation function, enabling the network to approximate complex functional mappings. Such a layered structure allows NNs to model intricate dependencies among features, making them particularly suitable when the data-generating process cannot be accurately described by simple linear models. During the training procedure, the choice of hyper-parameters of NNs strongly influences their performance. In particular, typical hyper-parameters are:

- *Number of hidden layers* that defines the depth of the network and its capacity to learn complex functions;
- *Number of neurons per layer* that controls the width of the network and the richness of the learned representations;
- *Activation functions* that determine the type of non-linearity introduced at each layer (e.g., rectifier function, logistic function and tangent function);
- *Learning rate* that governs the step size during the optimization process and strongly impacts convergence;
- *Number of epoch* that defines how many times the entire dataset is iterated during training;
- *Optimizer* representing the algorithm used to update the weights (e.g., gradient descent and Adam).

In our study, three key architectural hyper-parameters were tuned: the number of hidden layers, the number of neurons per layer, and the activation function. The optimal configuration was selected based on performance on validation data, after evaluating a total of 18 candidate models. Specifically, the number of hidden layers was varied within the set $\{1, 2, 3\}$, the number of neurons per layer within the set $\{32, 64\}$, and three activation functions were tested: rectifier (ReLU), logistic (sigmoid), and hyperbolic tangent (tanh). The best configuration resulted: 3 layers, 64 neurons and tanh as activation function. The optimizer was set to Adam, one of the most widely used and effective optimization algorithms. Training was performed for 1000 epochs, with the learning rate fixed at 0.001.

2.2.3. Model evaluation

After finding the best hyper-parameters, the model was trained on the entire training set and tested on the mentioned test set. The final results were expressed in terms of standard evaluation metrics. The *Mean Squared Error (MSE)* measures the average squared difference between the predicted and actual values:

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2, \quad (1)$$

where y_i and \hat{y}_i denote the true and predicted values, respectively. The MSE is non-negative ($\text{MSE} \geq 0$), and lower values indicate better predictive performance. The *Root Mean Squared Error (RMSE)*, defined as:

$$\text{RMSE} = \sqrt{\text{MSE}}, \quad (2)$$

provides an error measure in the same unit as the target variable, making it more interpretable. Hence, we will use RMSE instead of the simple MSE. RMSE is also non-negative, and smaller values correspond to better model accuracy. The *Mean Absolute Error (MAE)* computes the average absolute deviation:

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|, \quad (3)$$

which is less sensitive to outliers compared to MSE. MAE is non-negative and lower values indicate better predictions. Finally, the *Coefficient of Determination (R^2)* evaluates the proportion of variance in the target variable explained by the model:

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}, \quad (4)$$

where \bar{y} is the mean of the observed values. R^2 ranges from $-\infty$ to 1, with values closer to 1 indicating a better fit. A negative R^2 indicates that the model performs worse than a simple mean predictor. Together, these metrics provide a comprehensive understanding of model accuracy and generalization.

3. Experiments and Results

This section is devoted to presenting the results of the application of the designed NNR for bloodstain age estimation and a comparison of this approach to the state-of-the-art methods. In particular, the comparison involves multiple linear regression (MLR), multiple quadratic regression (MQR), support vector regression with gaussian kernel (SVMr), support vector regression with polynomial kernel (SVMp) applied in [10] and random forest regressor (RFR) applied in [11]. The comparison shown in Table 1 is carried out in terms of the aforementioned evaluation metrics: RMSE, MAE and R^2 .

Table 1

Results of our study on bloodstain age estimation. The best value for each metric is reported in bold.

Metrics	MLR	MQR	SVMr	SVMp	RFR	NNR
RMSE	3.9866	3.0414	2.4713	2.6322	2.1958	1.1802
MAE	3.3214	1.964	1.536	2.0000	1.3929	0.8214
R^2	0.7420	0.8498	0.901	0.8875	0.9217	0.9774

As shown in Table 1, NNR outperforms the state-of-the-art methods by considering all evaluation metrics.

4. Conclusions

In this study, we proposed a NNR approach for estimating the age of bloodstains based on colorimetric parameters. The results demonstrate that the proposed method outperforms existing state-of-the-art techniques in terms of predictive accuracy, as evidenced by lower error metrics and higher R^2 values on the test dataset.

Despite these promising results, several avenues for future work remain. First, the model could be further enhanced by incorporating additional features, such as environmental conditions (e.g., temperature, humidity, and surface type), which are known to influence bloodstain aging. Second, expanding the dataset with a larger number of samples and more diverse conditions would improve the network’s generalization capabilities. Finally, exploring more advanced architectures, including deep learning models with convolutional layers or attention mechanisms, could further improve predictive accuracy and robustness.

Overall, this work demonstrates the potential of neural network-based regression for forensic applications, offering a reliable approach for estimating bloodstain age.

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Declaration on Generative AI

The authors have not employed any Generative AI tools.

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