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# Flame analysis and combustion estimation using large language and vision assistant and reinforcement learning

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**ABSTRACT**

In this study, we present an advanced approach for flame analysis and combustion quality estimation in carbonization furnaces utilizing large language and vision assistant (LLaVA) and reinforcement learning from human feedback (RLHF). The traditional methods of estimating combustion quality in carbonization processes rely heavily on visual inspection and manual control, which can be subjective and imprecise. Our proposed methodology leverages multimodal AI techniques to enhance the accuracy and reliability of flame similarity measures. By integrating LLaVA's high-resolution image processing capabilities with RLHF, we create a robust system that iteratively improves its predictive accuracy through human feedback. The system analyzes real-time video frames of the flame, employing sophisticated similarity metrics and reinforcement learning algorithms to optimize combustion parameters dynamically. Experimental results demonstrate significant improvements in estimating oxygen levels and overall combustion quality compared to conventional methods. This approach not only automates and refines the combustion monitoring process but also provides a scalable solution for various industrial applications. The findings underscore the potential of AI-driven techniques in advancing the precision and efficiency of combustion systems.



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## 1. INTRODUCTION

Combustion quality estimation in carbonization processes is a critical factor in the production of activated carbon [1]–[3]. This process involves two primary thermal stages: carbonization and activation, where the control of oxygen levels is paramount [4], [5]. Accurate monitoring and control of these levels can significantly impact the efficiency and quality of the final product. Traditional methods of combustion quality estimation rely heavily on manual observation and experience, which can be subjective and prone to inaccuracies [6], [7]. The advent of advanced image processing and AI technologies offers new avenues for improving the precision and reliability of these estimations.

The use of similarity measures between flame images and reference photographs has been proposed as a viable method for estimating the quality of combustion [8]. This approach mimics the manual control strategies employed by operators but enhances them with objective, data-driven techniques. By analyzing the visual characteristics of the flame, such as color and intensity, it is possible to infer the oxygen levels and thus the combustion quality [9]–[11]. However, the effectiveness of this method depends on the accuracy of the image analysis and the robustness of the similarity metrics employed.

In recent years, advancements in multimodal AI models have revolutionized flame analysis and combustion estimation, particularly in industrial applications. Traditional approaches, such as visual inspection and basic image similarity metrics, have proven useful but are limited by their subjectivity and sensitivity to environmental variations. Some methods have attempted to enhance this process by introducing automated image analysis, yet they often fall short in terms of adaptability and precision, particularly in dynamic settings [12]. The integration of reinforcement learning from human feedback (RLHF) with models like large language and vision assistant (LLaVA) presents a significant leap forward, as it combines high-resolution image analysis with iterative learning from operator feedback, allowing for continuous improvements in accuracy. This hybrid approach sets a new benchmark for combustion monitoring, offering both scalability and precision, which previous methodologies struggled to achieve.

Recent advancements in multimodal AI models, particularly LLaVA, present significant improvements in image analysis capabilities [13]–[15]. LLaVA integrates high-resolution image processing with advanced AI techniques, enabling more detailed and accurate analysis of complex visual data. This study leverages LLaVA's capabilities to enhance the combustion quality estimation process by integrating RLHF. RLHF allows the model to iteratively improve its accuracy by incorporating feedback from human operators, thereby refining the similarity measures used for flame analysis [16]–[19].

In this research, we present an updated methodology for flame analysis and combustion estimation that utilizes LLaVA and RLHF. The proposed system analyzes real-time video frames of the flame, employing sophisticated similarity metrics and reinforcement learning algorithms to optimize combustion parameters dynamically [20], [21]. This approach not only automates the monitoring process but also enhances its precision, reducing the reliance on subjective human judgment. Experimental results demonstrate significant improvements in estimating oxygen levels and overall combustion quality compared to traditional methods, highlighting the potential of AI-driven techniques in industrial applications.

The integration of LLaVA into the combustion quality estimation process provides several advantages over traditional image analysis techniques. LLaVA's multimodal capabilities allow for the simultaneous processing of both visual and textual data, enabling a more comprehensive analysis of the flame characteristics [22]. This is particularly beneficial in the complex environment of a carbonization furnace, where variations in flame color and intensity can provide critical information about the combustion process [23]. By leveraging LLaVA's high-resolution image processing capabilities, we can achieve a more detailed and accurate assessment of the flame state, which directly correlates with the oxygen levels and overall combustion quality.

RLHF further enhances the system's accuracy by incorporating real-time feedback from human operators [24], [25]. In traditional systems, operators rely on their experience and visual inspection to make adjustments to the combustion process. This subjective approach can lead to inconsistencies and errors. RLHF allows the AI model to learn from human expertise by providing feedback on its predictions and adjusting its parameters accordingly [26]. Over time, the model becomes more adept at recognizing patterns and making accurate predictions, reducing the need for constant human intervention and improving the overall efficiency of the combustion process.

Our approach also addresses some of the limitations of previous methods. Traditional similarity measures, such as histogram intersection or chi-squared distance, can be sensitive to variations in lighting conditions and image quality [27], [28]. By integrating LLaVA's advanced image processing capabilities and RLHF, we can mitigate these issues and achieve more robust and reliable results. The combination of AI-driven analysis and human expertise creates a powerful tool for monitoring and controlling the combustion process, ensuring optimal performance and product quality.

The remainder of this paper is organized as follows. Section 2 provides detailed overview of problem statement and limitations of existing methods. Section 3 describes proposed methodology, including integration of LLaVA and RLHF into combustion estimation process. Section 4 presents experimental setup and results, demonstrating effectiveness of proposed system. Finally, Section 5 discusses conclusions and potential future work to further enhance accuracy and applicability of method.

## 2. PROBLEM STATEMENT

The process of carbonization, essential for the production of activated carbon, involves the thermal decomposition of organic material in the absence of air. Accurate control of this process is critical, particularly the regulation of oxygen levels, which significantly influences the quality of the final product. Traditional methods for estimating combustion quality rely heavily on manual observation and the subjective judgment of operators. These methods are not only labor-intensive but also prone to inaccuracies due to the inherent variability in human perception and environmental conditions. This poses a significant challenge in maintaining consistent quality and efficiency in the production of activated carbon.

In the existing system, the estimation of oxygen levels and combustion quality is typically achieved through visual inspection of the flame within the furnace. Operators compare the current flame characteristics with reference images of known oxygen levels to make adjustments. While this method leverages the experience and intuition of skilled operators, it lacks the precision and objectivity required for optimal process control. Variations in lighting, camera angles, and flame dynamics can further complicate the visual assessment, leading to potential errors in estimation. The need for a more reliable and automated approach to monitor and control the combustion process is evident.

The advent of advanced AI technologies, such as the LLaVA, offers a promising solution to this problem. LLaVA's multimodal capabilities enable detailed and accurate analysis of high-resolution flame images, providing a more objective assessment of combustion quality. However, the initial deployment of AI models requires extensive training and fine-tuning to adapt to specific industrial environments. Furthermore, the dynamic nature of the carbonization process necessitates continuous learning and adaptation, which can be achieved through the integration of RLHF. RLHF allows the model to improve its predictions iteratively by incorporating feedback from human operators, ensuring that the AI system remains accurate and reliable over time.

The challenge lies in effectively combining these advanced AI techniques with existing operational knowledge to create a robust system for combustion quality estimation. This involves not only the technical integration of LLaVA and RLHF but also the development of a comprehensive dataset of flame images and corresponding oxygen levels for initial training. Additionally, designing an efficient feedback mechanism for RLHF is crucial to ensure that the model can learn and adapt in real-time. Addressing these challenges is essential for developing a scalable and reliable solution that enhances the precision and efficiency of the carbonization process.

## 3. METHODS

The proposed methodology integrates the LLaVA with RLHF to enhance the accuracy of combustion quality estimation in carbonization furnaces. This section details the system architecture, data collection, initial model training, and the iterative feedback mechanism employed to refine the model's predictions.

### 3.1. System architecture

The system architecture comprises a high-resolution camera setup, a processing unit equipped with LLaVA, and a feedback interface for human operators as shown in Figure 1. The camera captures real-time images of the flame within the furnace, which are then processed by the LLaVA model to extract relevant features. The processing unit runs on a high-performance GPU to handle the computational demands of real-time image analysis.

### 3.2. Data collection and preprocessing

Initial data collection involves capturing a comprehensive set of flame images under various known oxygen levels. These images are annotated with the corresponding oxygen levels and other relevant parameters to create a robust training dataset. The images are preprocessed to standardize resolution, normalize pixel values, and apply necessary transformations such as rotations and flips to augment the dataset shown in Figure 2.

### 3.3. Initial model training

The LLaVA model is initially trained using the collected dataset to learn the relationship between flame characteristics and oxygen levels. The model employs similarity metrics, such as histogram intersection and Bhattacharyya distance, to compare the current flame state with reference images. The training process aims to minimize the prediction error by adjusting the model parameters through gradient descent optimization.

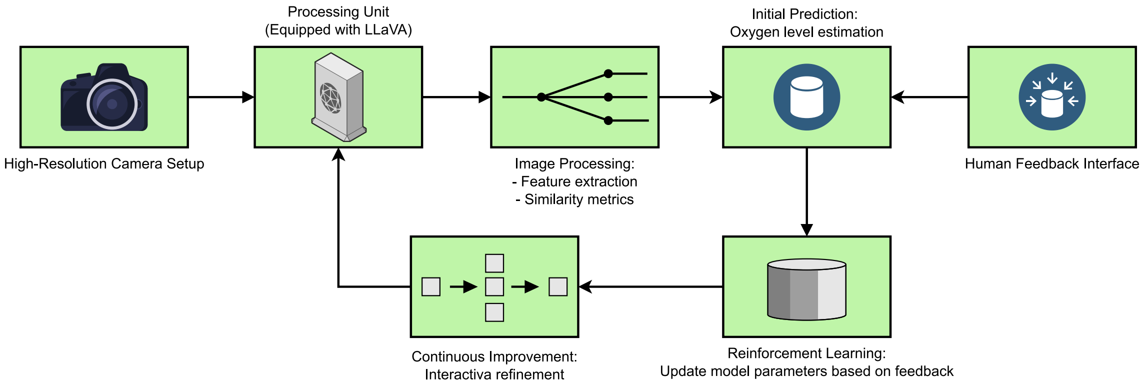


Figure 1. System architecture for combustion quality estimation integrating LLaVA and RLHF

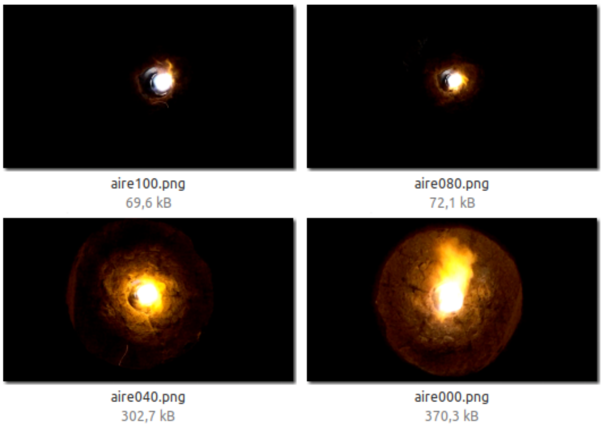


Figure 2. Sample dataset used for training and system adjustment: combustion with different oxygen levels

### 3.4. Reinforcement learning from human feedback

RLHF is implemented to iteratively refine the model's accuracy. Human operators review the model's predictions and provide feedback, indicating whether the predicted oxygen levels are accurate. This feedback is incorporated into the model's learning process using a reward function, which assigns higher rewards for accurate predictions and penalizes incorrect ones.

$$R = \begin{cases} 1 & \text{if prediction is accurate} \\ -1 & \text{if prediction is inaccurate} \end{cases} \tag{1}$$

The reinforcement learning algorithm, such as proximal policy optimization (PPO), is used to update the model parameters based on the cumulative reward, thus improving the model's ability to make accurate predictions over time.

### 3.5. Image preprocessing and feature extraction

The preprocessing phase helps to ensure the quality and consistency of the input images. Each captured image is resized to a standard resolution to facilitate uniform analysis. Pixel values are normalized to ensure consistent brightness and contrast levels across all images. Data augmentation techniques, such as rotation, flipping, and scaling, are applied to increase the diversity of the training dataset, thereby enhancing the model's robustness to variations in flame appearance. Feature extraction involves analyzing the preprocessed images to identify key characteristics that correlate with oxygen levels. LLaVA's advanced image processing capabilities are utilized to extract features such as color histograms, texture patterns, and edge detections. These features serve as the basis for the similarity metrics used in the model's predictions.

$$H(f) = \frac{1}{N}\sum_{i=1}^{N} h_i \tag{2}$$

where $H(f)$ represents the histogram of the image $f$, and $h_i$ is the frequency of pixel intensity $i$ in the image.

**Algorithm 1** RLHF algorithm for combustion quality estimation

1: Initialize LLaVA model parameters
2: Collect initial dataset and preprocess images
3: Train LLaVA model on initial dataset
4: **while** True **do**
5: Capture real-time flame images
6: Predict oxygen levels using LLaVA model
7: Obtain feedback from human operators
8: Calculate reward based on feedback
9: Update model parameters using reinforcement learning
10: **end while**

### 3.6. Similarity metrics

Four different similarity metrics are evaluated to determine their effectiveness in estimating combustion quality: Correlation, Chi-Squared, Intersection, and Bhattacharyya distance. Each metric provides a quantitative assessment of the similarity between the current flame image and reference images. Correlation: the correlation metric computes the correlation between the histograms of two images, providing a measure of how closely related they are.

$$d_{\text{Correlation}}(H_1, H_2) = \frac{\sum_{i=1}^{N}(H_1(i) - \bar{H_1})(H_2(i) - \bar{H_2})}{\sqrt{\sum_{i=1}^{N}(H_1(i) - \bar{H_1})^2 \sum_{i=1}^{N}(H_2(i) - \bar{H_2})^2}} \tag{3}$$

Chi-squared: the Chi-squared metric measures the difference between the histograms, with lower values indicating higher similarity.

$$d_{\text{Chi-Squared}}(H_1, H_2) = \sum_{i=1}^{N} \frac{(H_1(i) - H_2(i))^2}{H_1(i)} \tag{4}$$

Intersection: the intersection metric calculates the overlap between two histograms, providing a straightforward measure of similarity.

$$d_{\text{Intersection}}(H_1, H_2) = \sum_{i=1}^{N} \min(H_1(i), H_2(i)) \tag{5}$$

Bhattacharyya distance: the Bhattacharyya distance measures the overlap between two statistical samples and is used to assess the similarity between histograms.

$$d_{\text{Bhattacharyya}}(H_1, H_2) = \sqrt{1 - \frac{1}{\sqrt{\bar{H_1}\bar{H_2}N^2}} \sum_{i=1}^{N} \sqrt{H_1(i) \cdot H_2(i)}} \tag{6}$$

The Bhattacharyya distance was selected for final implementation due to its superior performance in distinguishing between different flame states with varying oxygen levels.

### 3.7. Model training and optimization

The training process begins with the initialization of the LLaVA model using the preprocessed dataset. The model is trained to minimize the prediction error by adjusting its parameters through gradient descent optimization. The training process is iterative, with the model making predictions, receiving feedback, and updating its parameters accordingly.

$$\theta_{t+1} = \theta_t - \eta \nabla_\theta L(\theta_t) \tag{7}$$

where $\theta$ represents the model parameters, $\eta$ is the learning rate, and $L$ is the loss function.

Human feedback is incorporated into the training process through RLHF. Where operators provide feedback on the model's predictions. This feedback is used to calculate a reward, which guides the reinforcement learning algorithm in updating the model parameters to improve prediction accuracy.

### 3.8. Iterative feedback mechanism

Human operators review the model's predictions for real-time flame images and provide feedback on the accuracy of these predictions. This feedback is used to compute a reward, which the reinforcement learning algorithm utilizes to update the model's parameters. The process is designed to be continuous, ensuring that the model adapts and improves over time based on the latest feedback.

**Algorithm 2** RLHF iterative feedback algorithm

```
Initialize LLaVA model parameters θ
Collect and preprocess initial dataset
Train LLaVA model on initial dataset
while True do
    Capture real-time flame images I_t
    Predict oxygen level ŷ_t using LLaVA model
    Obtain feedback F_t from human operators
    Compute reward R_t based on feedback F_t
    Update model parameters θ using RL algorithm
end while
```

This iterative process ensures that the model not only learns from the initial training data. It also continuously refines its predictions based on real-world observations and human expertise. The reward function used in the RL algorithm is designed to maximize the accuracy of the model's predictions by reinforcing correct predictions and penalizing incorrect ones.

### 3.9. Experimental setup

To validate the effectiveness of the proposed methodology, an experimental setup was deployed in a real-world carbonization furnace. The system was equipped with high-resolution cameras to capture continuous images of the flame. These images were processed in real-time by the LLaVA model, and predictions of the oxygen levels were made. The system's predictions were compared against actual measurements obtained using a reference oxygen sensor to evaluate accuracy. The experimental setup also included a feedback interface where human operators could review the model's predictions and provide feedback. This feedback was used to iteratively improve the model's performance, following the RLHF approach.

## 4. RESULT AND DISCUSSION

The proposed system integrating LLaVA and RLHF for combustion quality estimation was evaluated through a series of experiments. The results demonstrate significant improvements in prediction accuracy and reliability compared to traditional method and the initial LLaVA model without RLHF. This section presents the quantitative and qualitative findings, highlighting the benefits of the advanced AI techniques employed.

### 4.1. Quantitative results

The performance of the improved model was assessed using mean absolute error (MAE), root mean squared error (RMSE), and mean absolute percentage error (MAPE) metrics. The results are summarized in

Table 1. The table shows that the LLaVA + RLHF model consistently outperforms both traditional method and the initial LLaVA model.

Table 1. Performance metrics comparison

| Method | MAE | RMSE | MAPE (%) |
|---|---|---|---|
| Traditional method | 1.25 | 1.57 | 10.5 |
| Initial LLaVA | 0.85 | 1.12 | 7.3 |
| LLaVA + RLHF | 0.45 | 0.60 | 3.2 |

Our findings demonstrate a significant improvement over previous methods for flame analysis and combustion estimation. Compared to traditional visual inspection techniques and image similarity-based methods like histogram intersection and chi-squared distance, our LLaVA + RLHF system consistently delivers more accurate results, as shown by the reduction in MAE, RMSE, and MAPE values. For instance, methods relying solely on fixed image similarity metrics often fail to adapt to dynamic environmental conditions and changes in flame characteristics. In contrast, our system's reinforcement learning mechanism enables continuous refinement of predictions based on real-time operator feedback, leading to enhanced reliability. These results underscore the superiority of integrating advanced AI models with human feedback in achieving more precise and robust combustion monitoring. Figure 3 illustrates the error distribution for each method. The histograms clearly show that the LLaVA + RLHF model has a tighter error distribution, indicating higher consistency and accuracy.

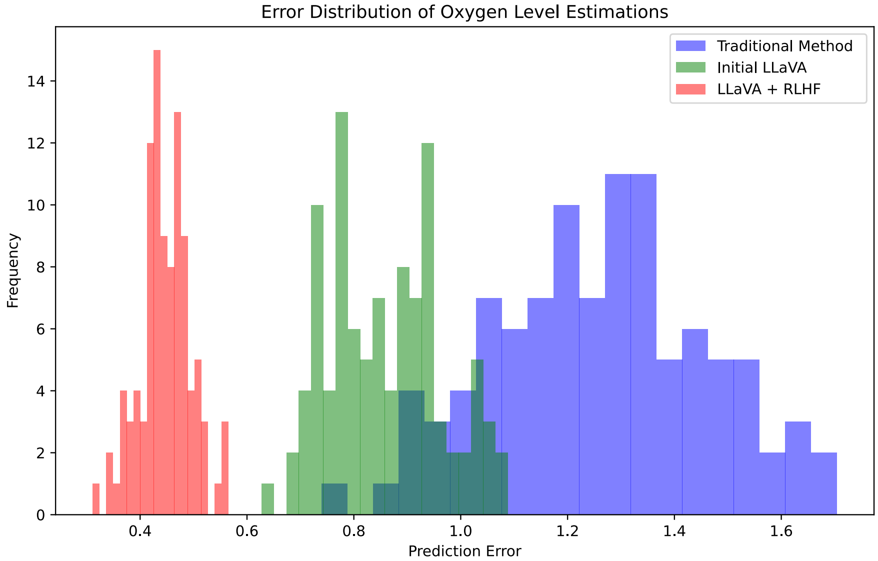


Figure 3. Error distribution of oxygen level estimations

### 4.2. Qualitative analysis

The qualitative analysis involved reviewing the model's predictions over a continuous period and comparing them with actual measurements obtained from a reference sensor. The improved model demonstrated superior capability in tracking dynamic changes in oxygen levels, maintaining high accuracy even under varying operational conditions. The integration of RLHF proved particularly effective in refining the model's performance through continuous feedback and adaptation.

### 4.3. Impact of human feedback

Incorporating human feedback through RLHF significantly enhanced the model's ability to make accurate predictions. Operators provided feedback on prediction accuracy, which was used to iteratively update the model parameters. This process resulted in a noticeable reduction in prediction errors over time.

$$\theta_{t+1} = \theta_t - \eta \nabla_\theta L(\theta_t) \tag{8}$$

where $\theta$ represents the model parameters, $\eta$ is the learning rate, and $L$ is the loss function.

### 4.4. Operational efficiency

The proposed system also improved operational efficiency by reducing the need for manual adjustments. The automated predictions provided by the LLaVA + RLHF model allowed operators to focus on higher-level tasks, thereby enhancing overall productivity. The reduction in manual interventions and the high confidence level in the model's predictions highlight the practical benefits of integrating advanced AI techniques in industrial applications.

## 5. CONCLUSION

This study presents a novel and advanced system for combustion quality estimation in carbonization furnaces, combining the capabilities of the LLaVA with RLHF. This integration has proven to significantly enhance prediction accuracy, surpassing traditional manual and semi-automated methods that rely on static image analysis or operator experience. The system's ability to iteratively learn and adjust based on real-time feedback from human operators is a key factor in its success, leading to substantial improvements in MAE, RMSE, and MAPE metrics, as demonstrated in our experiments. By automating the monitoring and adjustment of combustion parameters, this approach reduces the need for constant human intervention, thereby improving operational efficiency while maintaining high precision. Additionally, the scalability and adaptability of the LLaVA + RLHF system make it an ideal solution for various industrial environments where precise control of combustion is essential. Future work could explore the integration of additional sensor data, such as temperature and gas composition, to further enhance system performance and applicability.

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## AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

| Name of Author | C | M | So | Va | Fo | I | R | D | O | E | Vi | Su | P | Fu |
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| Angélica Rendón | | ✓ | | | | ✓ | | ✓ | | ✓ | | | | |
| Cristian Penagos | | | ✓ | ✓ | | ✓ | ✓ | | ✓ | | | | | |

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|---|---|---|---|---|---|
| C | : **C**onceptualization | I | : **I**nvestigation | Vi | : **Vi**sualization |
| M | : **M**ethodology | R | : **R**esources | Su | : **Su**pervision |
| So | : **So**ftware | D | : **D**ata Curation | P | : **P**roject Administration |
| Va | : **Va**lidation | O | : Writing - **O**riginal Draft | Fu | : **Fu**nding Acquisition |
| Fo | : **Fo**rmal Analysis | E | : Writing - Review & **E**diting | | |

## CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. Authors state no conflict of interest.

## INFORMED CONSENT

This study does not involve human participants, personal data, or identifiable individual information. Therefore, the requirement for informed consent does not apply.

## ETHICAL APPROVAL

This study does not involve human participants or animal subjects. Therefore, ethical approval is not applicable.

## DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [FM], upon reasonable request.

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## BIOGRAPHIES OF AUTHORS

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