Automatic Exam Score Extraction Using Computer Vision and Explicit Fuzzy Logic

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1   Introduction

Automatic extraction of handwritten information from scanned documents is a challenging problem due to the presence of noise, illumination variations, geometric distortions, and the intrinsic variability of human handwriting.

In academic evaluation systems, exam scores are often marked using checkbox grids. The interpretation of such markings cannot be reliably modeled using strict binary rules, as marks may be weak, ambiguous, partially erased, or affected by scanning artifacts.

This project proposes a robust and explainable solution based on classical computer vision techniques combined with an **explicit fuzzy logic decision framework**. The objective is not only to extract the score, but also to quantify the reliability of each decision.

2   Problem Definition

Given a scanned exam sheet containing a printed grading grid, the goal is to:

- Automatically locate the grading grid

- Detect the selected integer and decimal score components

- Handle ambiguous or noisy markings

- Produce a confidence score associated with the extracted result

The system must be robust to variations in resolution, orientation, lighting conditions, and marking styles.

3   System Overview

The proposed system follows a deterministic processing pipeline augmented by a fuzzy logic decision layer. This design ensures:

- interpretability of decisions,

- robustness to uncertainty,

- avoidance of black-box machine learning models.

4   Image Processing Pipeline

4.1   Image Acquisition and Orientation Correction

Input images are acquired as scanned copies (JPEG or PNG format). Orientation correction is performed using QR code detection when available. If the QR code is detected in the lower half of the image, a 180-degree rotation is applied automatically.

4.2 Relative Region of Interest Extraction

The grading grid is extracted using **relative coordinates** expressed as percentages of image dimensions. This approach guarantees scale invariance and robustness to resolution changes.

4.3 Adaptive Thresholding

Local adaptive thresholding is applied to convert grayscale images into binary representations. This technique effectively handles non-uniform illumination and background variations.

4.4 Morphological Processing

Two morphological operations are applied:

- Opening with a 3×3 kernel to remove small noise

- Closing with a 5×5 kernel to reconnect broken grid lines

Kernel sizes are selected empirically to preserve grid structure while eliminating artifacts.

4.5 Grid Detection via Projection Profiles

Horizontal and vertical projection profiles are computed from the binary image. Peaks in these profiles correspond to grid lines. Grouping of adjacent peaks enables robust line detection even in degraded scans.

4.6 Cell Segmentation

Grid intersections define individual score cells. Each cell is processed independently. Only the lower half of each cell is analyzed to avoid interference from printed text or grid labels.

5 Implicit Fuzzy Reasoning

Initially, uncertainty is handled implicitly through:

- relative comparison of ink densities,

- adaptive thresholds based on local statistics,

- heuristic decision rules.

While effective, this approach does not formally define fuzzy variables, membership functions, or inference rules.

6 Explicit Fuzzy Logic Modeling

To rigorously model uncertainty, an explicit fuzzy logic system is introduced.

6.1 Fuzzy Variables

The primary fuzzy variable is the *degree of marking* of a cell, quantified by its ink density $M_i \in \mathbb{R}^+$.

6.2 Universe of Discourse

The universe of discourse is defined dynamically as the set of ink densities observed within each sub-grid.

6.3 Membership Function

The degree of membership μ_i of cell i to the fuzzy set *"marked cell"* is defined as:

$$\mu_i = \frac{M_i - \bar{M}}{\max_j(M_j - \bar{M})}$$

where $\bar{M}$ is the mean ink density of the sub-grid.

This formulation ensures normalization in $[0, 1]$ and invariance to global intensity variations.

6.4 Fuzzy Rules

Decision-making is governed by explicit fuzzy rules, such as:

- IF one cell has a high membership degree AND others are low, THEN the cell is selected.

- IF two cells have similar membership degrees, THEN the decision is ambiguous.

- IF multiple cells have high membership degrees, THEN the result is rejected.

6.5 Inference and Defuzzification

Fuzzy inference evaluates the rules to identify candidate cells. Defuzzification is performed using the maximum membership principle:

$$i^* = \arg \max_i (\mu_i)$$

7 Confidence Score Computation

A confidence score is computed to quantify decision reliability.

Two criteria are considered:

- Maximum membership degree μ_{best}

- Relative separation between best and second candidates:

$$gap = \frac{M_{best} - M_{second}}{M_{best}}$$

The final confidence score is given by:

$$Confidence = \alpha \cdot \mu_{best} + \beta \cdot gap \quad \text{with } \alpha = 0.6, \ \beta = 0.4$$

8 Conclusion

The proposed approach demonstrates that explicit fuzzy logic provides a powerful and interpretable framework for handling uncertainty in document analysis tasks. The system avoids forced decisions and provides confidence-aware outputs suitable for academic evaluation workflows.