Development of a software system for verification of tactile surface relief for 3D-printed educational materials using convolutional neural networks

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Abstract

The article addresses the problem of automated verification of tactile surface relief quality in 3D-printed educational materials for blind users. A method for relief surface verification based on convolutional neural networks with a spatial attention mechanism is proposed, enabling effective recognition of texture features of printed tactile elements. The proposed method has been implemented as a software system that integrates with the additive manufacturing workflow, including a graphical user interface and a module for generating modified G-code. The effectiveness of the approach has been experimentally validated, achieving a classification accuracy of 94.7% on an independent test dataset. The practical significance of the results lies in enabling automated quality control of tactile products in accordance with BANA and ISO standards.

Keywords

tactile graphics, 3D printing, convolutional neural network, relief verification, inclusive technologies, blind users, additive manufacturing

1. Problem Statement

Ensuring equal access to educational resources for individuals with visual impairments remains one of the priority directions in the development of inclusive technologies [1, 2]. According to the World Health Organization, as of 2023, more than 2.2 billion people worldwide experience some form of visual impairment, of whom approximately 43 million are completely blind [3, 4]. Traditional methods for producing tactile educational materials, including thermoforming and microcapsule paper technologies, are characterized by high production costs, limited flexibility, and long manufacturing cycles [5, 6].

The widespread adoption of additive manufacturing technologies offers fundamentally new opportunities for the fabrication of individualized tactile objects with predefined geometric relief parameters [5, 7]. However, the lack of standardized quality control tools for assessing printed surface characteristics hinders the large-scale integration of these technologies into educational practice. Manual verification of tactile relief compliance with established standards is time-consuming and relies on subjective expert judgment, making it difficult to ensure consistent product quality [8, 9].

The relevance of this study is driven by the need to develop automated verification tools capable of evaluating tactile relief quality in real time and integrating seamlessly with the 3D printing process. The application of machine learning methods, particularly convolutional neural networks,

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opens up prospects for creating objective quality control systems that are invariant to lighting conditions and surface viewing angles [10, 11].

2. State of the Art and Related Work

The issue of quality control automation in additive manufacturing has been actively investigated over the past decade. Wang et al. (2020) [10] proposed an adaptive surface monitoring system for fused deposition modeling based on convolutional neural networks, achieving defect detection accuracy of 92.4%. Fastowicz and Okarma (2018) [12] developed a method for assessing the quality of 3D-printed surfaces using structural similarity of image fragments; however, their approach does not account for the specific requirements of tactile materials.

In the work by Götzelmann (2016), the concept of LucentMaps [7] was introduced—3D-printed audiovisual tactile maps incorporating capacitive markers for interaction with smartphones. Studies by Holloway, Marriott, and Butler (2018) [5] demonstrated the advantages of 3D-printed models over traditional tactile graphics in navigation tasks performed by blind users. Leporini et al. (2020)[13] formulated design guidelines for interactive 3D models of cultural heritage objects intended for people with visual impairments.

Research conducted by the Baylor University group (Shaw et al., 2022 [14]), published in Science Advances, demonstrated the feasibility of creating tactile lithophanes for scientific data visualization by blind researchers. The accuracy of tactile interpretation among blind participants reached 96.7%, exceeding the visual interpretation performance of sighted individuals. The ICCHP 2024 conference highlighted a growing interest in the automatic generation of tactile graphics; in particular, studies by Narcisi et al. as well as Watanabe and Minatani focused on the development of accessible interaction interfaces for tactile models. [15]

An analysis of the scientific literature indicates that existing studies predominantly focus on the design of tactile objects and the development of interaction interfaces, whereas the problem of automated verification of tactile relief quality remains insufficiently explored. Comprehensive software solutions capable of classifying the quality of printed relief in accordance with BANA (Braille Authority of North America) tactile graphics standards and integrating with 3D printer control systems are currently lacking.

3. Research Objective

The objective of this study is to develop a software system for the verification of tactile surface relief in 3D-printed educational materials using convolutional neural networks, with a focus on automated assessment of surface quality.

To achieve this objective, the following tasks are addressed:

1. to analyze tactile graphics standards and identify relief quality criteria suitable for automated classification;
2. to design a convolutional neural network architecture optimized for recognizing the textural features of printed surfaces;
3. to develop a modified G-code generation module for producing predefined types of relief textures;
4. to experimentally verify the effectiveness of the proposed system using a test dataset comprising samples of varying quality.

4. Methodology

According to the guidelines of the Braille Authority of North America (*Guidelines and Standards for Tactile Graphics*, 2022), the height of tactile graphic elements should range from 0.25 to 1.0 mm depending on the manufacturing technology [8]. For thermoformed maps, the recommended relief height is at least 1 mm, whereas for microcapsule paper it is approximately 0.5 mm. A study by Jehoel (2009) established that the optimal height of tactile elements lies in the range of 40–80 μm, depending on the background texture and object shape [6].

The Americans with Disabilities Act (ADA) standard specifies a minimum height of raised characters of 0.8 mm (1/32 inch) [16]. Braille dots must comply with the following parameters: height of 0.25–0.53 mm, base diameter of 1.2–1.6 mm, inter-dot spacing within a cell of 2.3–2.5 mm, and inter-cell spacing of 6.0–6.2 mm. Deviations from these parameters result in a significant deterioration of tactile legibility [8].

Based on the analysis of existing standards, a four-level relief quality classification scheme was formulated: excellent (compliance coefficient ≥ 0.85), good (0.70–0.84), acceptable (0.55–0.69), and poor (< 0.55). The compliance coefficient is computed as a weighted sum of normalized metrics, including contrast, texture uniformity, edge sharpness, relief depth, and surface roughness. The weighting coefficients were determined experimentally using correlation analysis with expert assessments.

The proposed TactileReliefCNN architecture is based on a five-block convolutional structure with a progressive increase in the number of filters: 32 → 64 → 128 → 256 → 512. Each block consists of a convolutional layer with a 3×3 kernel, followed by batch normalization and a ReLU activation function, after which a 2×2 max-pooling operation is applied.

A key feature of the architecture is the Spatial Attention Module, integrated after the final convolutional block. The module comprises two sequential 1×1 convolutional layers that reduce the number of channels to 64 and subsequently to 1, with a sigmoid activation applied at the output. The resulting attention map is multiplied element-wise with the feature tensor, enabling the model to emphasize regions exhibiting pronounced textural characteristics of the relief.

The network's classification head consists of three fully connected layers with intermediate dimensionalities of 1024 and 256 neurons. Dropout regularization with rates of 0.5 and 0.3 is applied to mitigate overfitting. In parallel, a regression head is employed to estimate the normalized relief height; it comprises two fully connected layers with a sigmoid activation function at the output.

The loss function is defined as a combination of cross-entropy loss for the classification task and mean squared error for relief height regression:

$$L = L_{CE}(\hat{y}, y) + \lambda \cdot L_{MSE}(\hat{h}, h), \tag{1}$$

where L_CE denotes the cross-entropy loss, L_MSE - denotes the mean squared error, ŷ and ĥ represent the predicted class label and relief height, respectively, while y and h correspond to the ground-truth values. The parameter λ=0.3 is the weighting coefficient of the regression component.

Weight initialization is performed using the Kaiming method for convolutional layers and a normal distribution with a standard deviation of 0.01 for fully connected layers. Optimization is carried out using the Adam algorithm with an initial learning rate of 0.001 and exponential decay.

The TextureGenerator module implements control code modification algorithms for generating six basic types of relief patterns: smooth surfaces, dotted textures, linear reliefs, wave patterns, mosaic structures, and Braille dots. For each texture type, optimal printing parameters are defined, including travel speed, extruder temperature, layer height, line width, and infill percentage.

The Braille dot generation algorithm produces hemispherical elements using spiral infill with a gradual reduction of the radius at each successive layer. The dot parameters comply with BANA standards: a height of 0.5 mm, a diameter of 1.5 mm, and an inter-dot spacing of 2.5 mm. The control code is generated in a format compatible with most FDM printers (Marlin, RepRap).

In parallel with the neural network classifier, a ReliefAnalyzer module was developed to implement classical image processing methods for relief quality assessment. The module computes five metrics: contrast (normalized Michelson contrast coefficient), texture uniformity (based on brightness histogram entropy), edge sharpness (variance of the Laplacian operator), relief depth (mean Sobel gradient magnitude), and surface roughness (an Ra-like metric) [1, 12].

Contrast is computed using the Michelson formula:

$$C=(I_{max}-I_{min})/(I_{max}+I_{min}), \quad (2)$$

where *I*_max and I_min denote the maximum and minimum brightness values in the image, respectively.

Texture uniformity is quantified using normalized entropy:

$$U=1-H(p)/8, \quad (3)$$

where H(p) = -Σ p_i $\log_2$(p_i) denote the maximum and minimum brightness values in the image, respectivelydenotes the Shannon entropy of the brightness histogram.

For training and testing the neural network, a dataset comprising 4,800 images of relief surfaces was constructed. The samples were produced using an FDM printer (Creality Ender-3 V2) with PLA filament. The dataset covers four quality classes with a uniform distribution of 1,200 images per class. All images were captured using a 2-megapixel USB microscope under standardized lighting conditions.

The dataset was split into training, validation, and test subsets using a 70:15:15 ratio. Data augmentation techniques were applied, including random rotation (±15°), horizontal flipping, brightness variation (±20%), and contrast adjustment (±15%) [10, 13].

5. Results and Discussion

This section presents the results of the experimental evaluation of the proposed TactileReliefCNN-based system for automated verification of tactile surface relief quality. The performance of the model is assessed using standard classification metrics on a test dataset, with a focus on its ability to distinguish between different levels of relief quality. Additionally, the behavior of the model and its practical applicability are analyzed.

The experimental results are summarized in Table 1.1.

Quality Class	Precisiony	Recall	F1-score
Excellent	0,962	0,951	0,956
Good	0,938	0,944	0,941
Acceptable	0,925	0,931	0,928
Poor	0,958	0,963	0,960
Macro-average	0,946	0,947	0,946

The overall classification accuracy on the test dataset reaches 94.7%. The highest performance is achieved for the excellent and poor quality classes, which can be attributed to the more distinct visual differences characteristic of these extreme categories. The acceptable class exhibits slightly lower metric values due to the intermediate nature of its visual features.

Analysis of the attention maps indicates that the model focuses on regions with pronounced relief transitions, edges of textural elements, and areas of non-uniform infill. This behavior is consistent with expert-based criteria used for tactile surface quality assessment.

Model convergence is achieved at approximately the 35th training epoch, after which the evaluation metrics stabilize. The gap between training and validation loss remains negligible, indicating the absence of overfitting due to the applied regularization techniques.

The developed system is implemented in Python 3.10 using the PyTorch 2.0 library for the neural network module, OpenCV 4.8 for image processing, PyQt5 for the graphical user interface, and Matplotlib for data visualization. The graphical user interface consists of five functional tabs: relief verification, G-code generation, model training, result analysis, and system settings (Figs. 1–3).

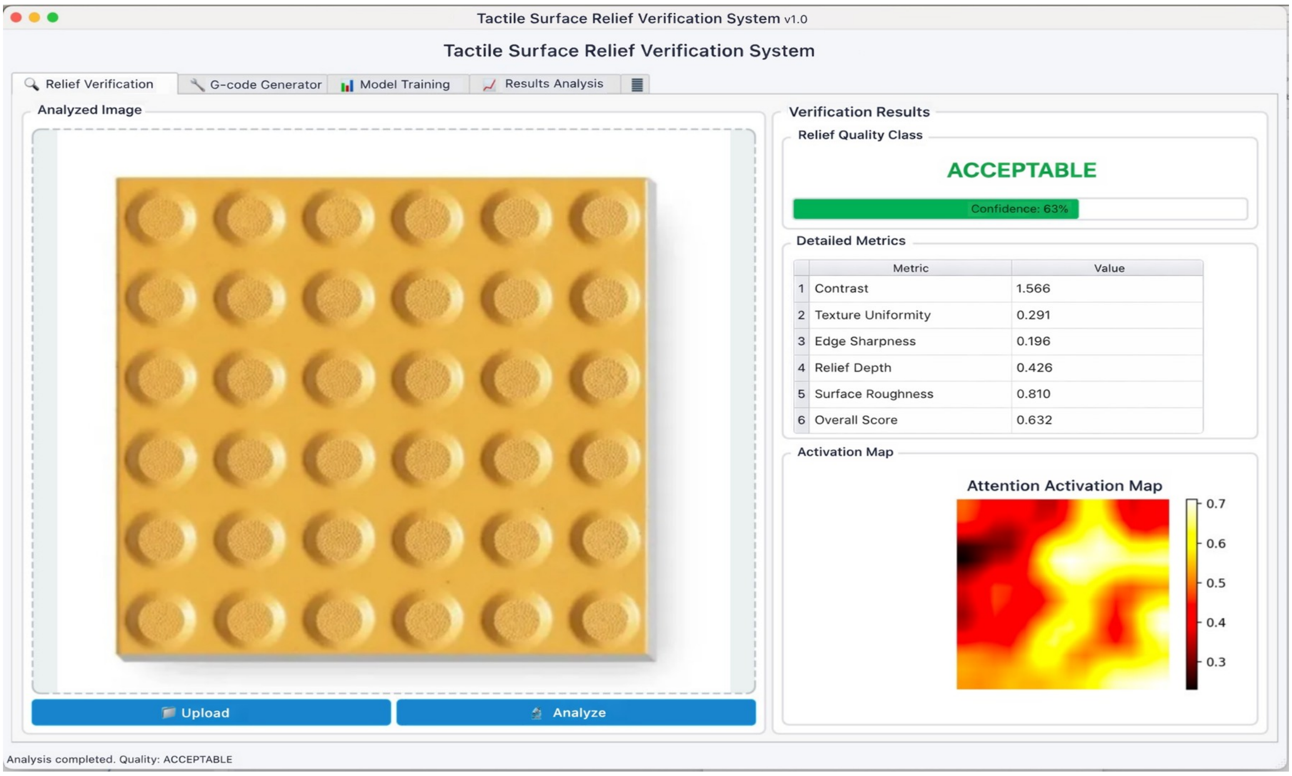

Figure 1: Implemented system and its operational workflow during image analysis.

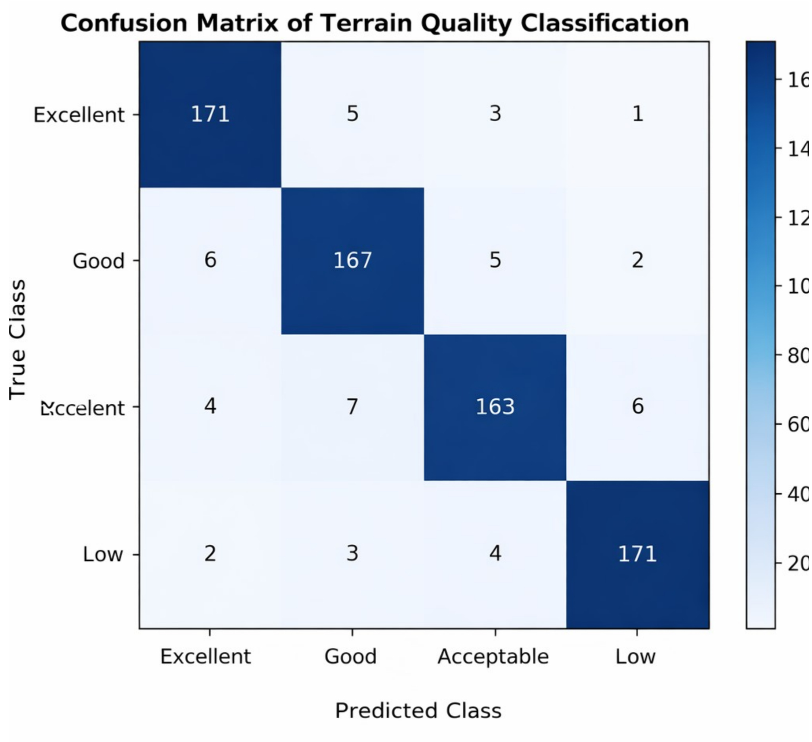

Figure 2: Confusion matrix for relief quality classification.

Figure 3: Model Training.

The verification tab enables loading an image of a relief surface and performing its analysis, displaying the predicted quality class, confidence score, detailed evaluation metrics, and the corresponding attention activation map. The G-code generator tab allows the user to select the texture type, specify the relief height and printing speed, upload an input G-code file, and obtain its modified version.

The training module supports hyperparameter configuration, including the number of epochs, learning rate, and batch size, as well as real-time visualization of training curves and saving the trained model in the PyTorch format. The analysis tab aggregates verification statistics and provides visualizations of class distributions and score histograms.

The obtained results also indicate several directions for future research. In particular, further improvements may include expanding the dataset with samples from different 3D printing technologies, enhancing the robustness of the model under varying acquisition conditions, and exploring additional architectural modifications. Moreover, the proposed approach can be extended to other application domains involving surface quality assessment in additive manufacturing.

6. Conclusions

This work presents a software system for the automated verification of relief surface quality in 3D-printed tactile materials. A convolutional neural network architecture, TactileReliefCNN, incorporating a spatial attention mechanism and optimized for recognizing textural characteristics of printed reliefs, is proposed. The effectiveness of the developed approach is experimentally validated: the classification accuracy on the test dataset reaches 94.7%, while the F1-score for all quality classes exceeds 0.92.

A modified G-code generation module was developed to produce six basic types of relief textures with parameters compliant with BANA tactile graphics standards. In addition, a graphical user interface was implemented to integrate all system components and provide intuitive operator interaction.

The practical significance of the obtained results lies in the potential to automate quality control in the production of tactile educational materials, thereby enhancing educational accessibility for individuals with visual impairments. Future research directions include expanding the dataset to cover additional printing technologies (SLA, SLS), integrating the system with industrial-grade 3D printers, and conducting user studies involving focus groups of blind participants.

Declaration on Generative AI

During the preparation of this work, the author(s) used AI tools in order to: Grammar and spelling check.

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