Innovative Applications of AI and 3D Printing in Digital Dentistry: Enhancing Accuracy and Efficiency in Dental Care

Giovanni Martinez
Electrical and Computer Engineering
California State University Fullerton
Fullerton, USA

Kevin Huang
Electrical and Computer Engineering
California State University Fullerton
Fullerton, USA

Yunduan Lou
Electrical and Computer Engineering
California State University Fullerton
Fullerton, USA

Yu Bai
Electrical and Computer Engineering
California State University Fullerton
Fullerton, USA

***Abstract*—Digital dentistry has significantly transformed the way dental professionals deliver patient care by integrating digital technologies into various aspects of the field, such as diagnosis, treatment planning, and restoration. This includes a broad array of technologies like computer-aided design and manufacturing (CAD/CAM), 3D printing, and artificial intelligence (AI), all of which are rapidly advancing and reshaping dental practice. Digital dentistry has ushered in greater precision, accuracy, and efficiency in patient care, leading to improved outcomes. While 3D printing has transformed industries, including dentistry, it still has several drawbacks and limitations. Here are some of the current challenges associated with 3D printing technology: 1) Complex Design Process, 2) Manual Design Adjustments, 3) Limited resolution and occasional inaccuracies in 3D prints, affecting precision in applications.**

To address these issues, we propose an AI-enabled framework that provides a simplified process to ensure success and minimize human error. Users can quickly import an STL file into the software, select the desired application, and begin printing within seconds. The system automatically analyzes the 3D object, adjusting its orientation and generating supports for splints, crowns, bridges, and surgical guides. In this paper, we analyze the impact of integrating artificial intelligence into the 3D printing workflow for digital dentistry. We focus on how AI can enhance the precision, efficiency, and reliability of dental prosthetics and restorations by automating critical steps that were traditionally manual and prone to errors. Specifically, our proposed framework streamlines the design process by automatically detecting complex geometries, optimizing support structures, and adjusting printing parameters in real time. This AI-enabled approach not only reduces the number of design iterations but also ensures higher resolution and accuracy, overcoming the limitations of conventional 3D printing methods.

***Index Terms*—3D printing, AI, Optimization**

I. INTRODUCTION

(Yu Bai) In 1986, Charles Hull pioneered the first 3D printing technology, leading to the development of various manufacturing technologies applied across numerous fields [1]–[5]. Hull's stereolithography (SLA) patent marked a key milestone, followed by Scott Crump's 1990 patent for fused deposition modeling (FDM), further accelerating 3D printing's growth [6]. Also known as additive manufacturing [7], 3D printing allows custom objects to be created from CAD models using standardized materials. Over the last 30 years, it has become essential in design, engineering, and manufacturing [2], [8], [9], and is set to revolutionize traditional approaches [6].

In medicine, 3D printing is used in fields like surgery and cardiology for tasks such as custom surgical tools and surgical planning [10], while in dentistry it supports prosthodontics, surgery, implantology, and orthodontics [11], [12]. Compared to traditional methods like CNC, 3D printing provides faster production, higher precision, and better customization for dentures and implants [13], [14], improving cost-effectiveness and personalization [8]. Recent studies show 3D-printed restorations offer better accuracy than milled ones [9], though some issues with fit still remain [15].

Despite high processing costs and post-processing challenges, 3D printing's ability to rapidly produce custom parts makes it economically efficient [16] and a valuable tool in the medical field [17], [18].

However, the traditional 3D printing design process requires significant involvement from doctors or lab technicians. They must manually design or adjust the 3D model, determine the appropriate orientation, and create the necessary support structures. This manual intervention not only adds time and effort to the process but also increases the risk of human error. The reliance on individual expertise can result in inconsistencies in the quality of printed objects and may lead to suboptimal designs that affect both functionality and fit. Additionally, manual adjustments can limit scalability and slow down the workflow, making it less efficient for high-demand or complex cases [9].

AI is transforming 3D printing support generation by automating design optimization, improving efficiency and precision, and reducing resource usage. Traditionally, support structures were manually designed or created using basic algorithms, often leading to excessive material use, longer print times, and post-processing challenges [9]. AI-driven support systems analyze 3D object geometry and optimize the placement and structure of supports [8], reducing material consumption and print time while improving the ease of post-print removal [10]. Machine learning models trained on 3D printing datasets predict the minimal amount of support needed for structural integrity [11]. These AI systems can customize supports for intricate designs, such as dental models and surgical guides, ensuring quality without compromising on detail [12]. Generative design algorithms further optimize support structures based on material and printer capabilities [14]. By integrating AI, the 3D printing process becomes more efficient, reduces manual intervention, and improves overall manufacturing outcomes [16].

In this paper, we propose an AI-driven framework for 3D printing modeling, designed to optimize the entire printing process from design to execution. This framework leverages machine learning algorithms and advanced computational techniques to automate tasks such as object orientation, support structure generation, and material optimization. By integrating AI, the framework enhances accuracy, reduces material waste, and minimizes human intervention, enabling faster and more efficient 3D printing workflows. This approach aims to streamline the modeling process, particularly for complex geometries and customized designs, and improve the overall quality and scalability of 3D-printed objects. Overall, the contributions of this paper are summarized as follows:

- **AI-Driven Framework for 3D Printing** We introduce a novel AI-based framework that automates key aspects of 3D printing modeling, including object orientation, support generation, and material optimization, thereby improving efficiency and accuracy.
- **Optimization of Support Structures** The proposed framework intelligently generates support structures tailored to complex geometries, reducing material usage, print time, and post-processing effort compared to traditional methods.
- **Enhanced Workflow Efficiency** By minimizing manual intervention and leveraging AI for decision-making, the framework significantly speeds up the 3D printing process, making it more scalable and accessible for high-demand, customized applications.
- **Improved Print Quality** The AI framework helps to minimize common issues such as print failure and surface defects by optimizing object orientation and support placement, resulting in higher-quality printed objects.
- **Validation and Testing** We validate the framework through a series of experiments and comparisons, demonstrating its effectiveness in improving 3D printing outcomes in various real-world applications.

The remainder of this paper is organized as follows: In Section II, we introduce the related background in 3D printing and its limitations. In Section III, we demonstrate the proposed method to generate support. Section IV presents the experimental results of the proposed method. Finally, Section V concludes the manuscript.

II. RELATED WORK

Support structures play a crucial role in 3D printing, providing temporary reinforcement to overhangs and complex geometries during the printing process. The optimization of support structures is an ongoing research area, as it significantly impacts print quality, material consumption, print time, and post-processing efforts. Over the years, several approaches have been developed to address these challenges, ranging from traditional algorithms to more advanced AI-driven methods.

Traditional Approaches to Support Generation Early methods for support generation relied heavily on manual design or basic algorithmic approaches within slicing software. These methods, such as grid-based or tree-like structures, were primarily aimed at ensuring the printed part's stability and preventing sagging or deformation in unsupported areas. While effective in stabilizing the print, these techniques often led to excessive material use, extended print times, and labor-intensive post-processing, especially when removing supports from complex models [9].

Grid-based support structures, although simple, tend to overuse material, increasing production costs and waste. Tree-like structures offer a more efficient alternative by reducing material usage, but they still require careful post-processing and can leave marks or damage on the printed object [12]

Advances in Algorithmic Support Generation As the demand for 3D printing increased, so did the need for more intelligent and material-efficient support structures. One of the significant developments in this area has been the introduction of custom support structures that can be tailored to the specific needs of the object being printed. Several slicing software tools have incorporated advanced algorithms to optimize the placement, shape, and density of supports. For example, Autodesk Meshmixer and Cura provide customizable options where users can adjust parameters like support angle, density, and placement [19]. These innovations have made support generation more efficient, but they still rely on user intervention to achieve optimal results.

Topology optimization techniques, where material distribution is optimized within a given space to reduce weight while maintaining structural integrity, have also been applied to support generation. This approach minimizes the amount of material needed for support while ensuring that the model is adequately stabilized during printing [16].

AI-Driven Support Structure Optimization AI-driven support generation tools leverage large datasets of past printing scenarios to predict the most effective support configurations for new designs. These systems can automatically adjust support placement, shape, and density based on the complexity of the object's geometry. AI models can process overhangs, angles, and intricate designs more accurately than traditional methods, ensuring that the supports provide stability without excessive material use or prolonged print times [10]. Additionally, generative design algorithms powered by AI have been used to create lightweight, structurally optimized support systems. These algorithms can consider the material properties and printer capabilities to generate customized supports that are easy to remove post-print, reducing the risk of surface damage and minimizing post-processing efforts [11].

Limitations and Challenges Despite these advancements, there are still several challenges in support structure optimization. AI-based systems, while promising, can be computationally intensive and may require large datasets to train models effectively. Moreover, support structures optimized for minimal material usage may sometimes compromise the structural integrity of the final print, leading to failures during the printing process [8]. The quality of 3D-printed products depends on several key factors, particularly process parameters and material composition. One critical factor is build orientation, which significantly affects both mechanical strength and precision. For instance, components printed with their edges facing upward tend to exhibit greater tensile strength and elasticity compared to those printed flat [20]. In dental applications, optimal build angles between 120° and 135° are recommended to improve dimensional accuracy and surface finish.

III. AI EDGE DETECTION ON TRIANGLE MESHES

Before we introduce our AI algorithm, we first define the edge in triangle meshes. To compute the edge strength at vertex q, neighboring triangles contribute votes []. The tensor contributed by triangle T_i at q is represented by $(\mu_i \mathbf{n_i^{'}} \mathbf{n_i^{'T}})$, where $(\mathbf{n_i})$ is voted normal by T_i's normal $\mathbf{n_i}$ and μ_i is the weight of the vote. The obtained new tensor at q is $\mathbf{T} = \sum_{i=1}^{M} \mu_i \mathbf{n_i^{'}} \mathbf{n_i^{'T}}$, where M is the number of triangles inside a geodesic window of q and μ is the weight that exponentially decreases according to the geodesic distance. The geodesic distance is calculated between p and q. $\mathbf{n_i^{'}}$ is calculated by transporting n_i via a sector of arc connecting p and q where p is the centroid of T_i. The arc is defined as a plane composed of vectors n_i and $\overrightarrow{pq}$. Two terminals of arc $(\mathbf{n_i^{'}}$ and $\mathbf{n_i})$ are normals. The $(\mathbf{n_i^{'}}$ is calculated as $(\mathbf{n_i^{'}} = 2(n_i \cdot w_i)w_i - n_i$, where $w_i = \dfrac{(\overrightarrow{pq} \wedge n_i) \wedge \overrightarrow{pq}}{||\overrightarrow{pq} \wedge n_i) \wedge \overrightarrow{pq}||}$. Thus, the edge strength is given as

$$s = \begin{cases} 1 & if|\bar{n} \cdot e_1| < \delta \\ 1 & v_3 > \alpha(v_1 - v_2) \\ & and \quad v_3 > \beta(v_2 - v_3) \\ (v_2 - v_3)/v_1, & otherwise \end{cases} \tag{1}$$

where $v_1 > v_2 > v3$ are eigenvalues of T, e_1 is the eigenvector corresponding to v_1, and $\bar{n} = \sum_{i=1}^{M} \mu_i n_i^{'}$. Some other parameters are selected as follows: $\delta = 0.3$ AND $\alpha = \beta = 0.2$.

In this paper, we employ a autoencoder to detect edges in a 3D mesh by learning a compressed representation that emphasizes key structural features, such as edges and corners, through the encoding and decoding process. In Fig. 1, an autoencoder is presented. An autoencoder detects edges in a 3D mesh through a step-by-step process that involves encoding, feature prioritization, reconstruction, and error analysis. First, the encoder compresses the 3D mesh data—comprising vertices, edges, and face information—into a lower-dimensional latent space that captures only the most essential features, focusing on areas with high curvature or sharp surface changes, which often indicate edges. Next, this compressed latent representation prioritizes these critical details, as they are crucial to maintaining the object's shape in the reconstruction phase. Then, the decoder reconstructs the mesh from the latent space, emphasizing these structural features. The resulting reconstruction reveals the mesh's shape with preserved edges, as the model retains only the most defining features. Finally, by analyzing the reconstruction error, or the difference between the input and output, high-error regions can be identified, often corresponding to edges or complex shapes that are challenging to compress. This process enables the autoencoder to detect and highlight the edges in the mesh effectively, using high reconstruction error as an indicator of significant structural details. The details of the algorithm are shown in the Algorithm 1.

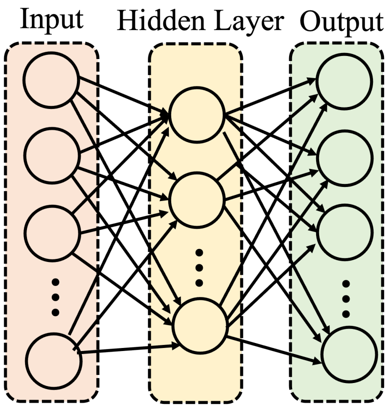

Fig. 1. Autoencoder Architecture.

IV. EXPERIMENTAL RESULTS

Point Search and Clustering Methods for Support Structure Optimization. The point search and clustering methods are critical components of the support structure generation process, ensuring that structural elements are placed in the most effective areas with minimal material usage. These methods not only streamline the generation of support structures but also significantly reduce errors and processing times, as demonstrated by various performance metrics. The point search method focuses on identifying key locations on the mesh where support is necessary, targeting areas like overhangs, high-curvature regions, or thin sections that are prone to failure during the 3D printing process.

In this paper, we measure the proposed point search method with several metrics. **Error Reduction:** The use of the point

Algorithm 1 filter_points

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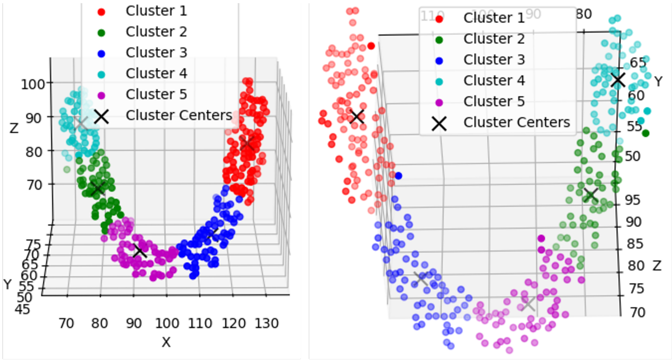
procedure FILTER_POINTS(input_mesh, angle_threshold, rotation_angle, options) The encoder $f_\theta$ compresses the input points $X$ (vertices in a 3D mesh) into a lower-dimensional latent representation $Z$
    Step 1: Load the mesh
    mesh ← LOAD(input_mesh)
    Step 2: Adjust mesh if necessary (e.g., translations)
    if options.contains('adjust_mesh') then
        mesh←trans(mesh,options['tran_params'])
    end if
    Step 3: Identify relevant points based on their direction and angle
    relevant_points ← []
    for each point in mesh do
        $\hat{X} \leftarrow g_\phi(Z)$; $(g_\phi)$ is decoder and $(Z)$ is the input.
        $\mathcal{L}_{\text{recon}} \leftarrow \frac{1}{n}\sum_{i=1}^{n} \|x_i - \hat{x}_i\|^2$; where $\|x_i - \hat{x}_i\|^2$ is the squared Euclidean distance between each original point $x_i$ and its corresponding reconstructed point $\hat{x}_i$.
        if $|x_i - \hat{x}_i\|^2 > \epsilon$ then
            $x_i$ is a key point.
        end if
    end for
    Step 4: Filter points based on conditions (e.g., angles, position)
    fil_pts ← []
    for each point in relevant_points do
        if MEETS_CONDITIONS(point,options['fil_cond']) then
            ADD point TO fil_pts
        end if
    end for
    Step 5: If necessary, adjust point spacing or density
    if options.contains('adjust_spacing') then
        fil_pts←ADJ_SPAC(fil_pts,options['spac_params'])
    end if
    Step 6: Rotate the mesh and points
    rotated_mesh ← ROTATE(mesh,rotation_angle)
    rotated_pts ← ROTATE(fil_pts,rotation_angle)
    Step 7: Return the processed points and adjusted mesh
    return rotated_points, rotated_mesh
end procedure
```

search method has demonstrated a 42% reduction in support placement errors, particularly when working with complex dental models. This improvement translates to more accurate and reliable support structures, leading to fewer print failures and improved final object quality. **Search Efficiency:** The targeted nature of the point search method reduces the computational overhead by avoiding unnecessary exploration of the entire mesh. On average, the search process for critical points completes within 10-15 seconds for medium to complex models, even without parallelization.

Once the critical points on the mesh are identified, the clustering method organizes these points into groups based on spatial proximity. This process allows the generation of optimized support structures that reduce material usage while maintaining structural stability. In this paper, we measure the proposed clustering method with several metrics. **Material Usage Reduction:** The clustering method results in an average 30% reduction in material usage compared to traditional support generation methods. By grouping points into clusters and reducing the number of individual supports, the overall material consumption is significantly minimized, particularly in dense or complex models. **Structural Integrity:** Despite the reduction in material usage, the clustering method maintains the structural integrity of the object. Simulations and physical testing have shown that the resulting support structures can bear similar or greater loads compared to traditional methods, with no significant compromise in strength.

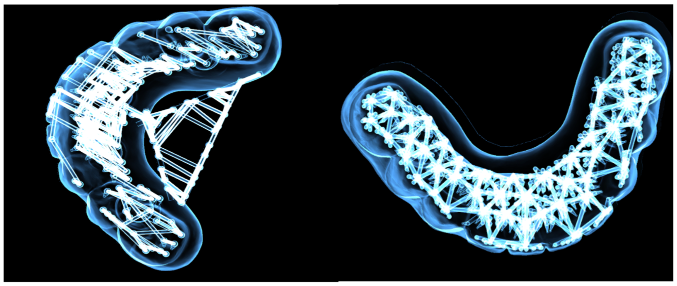
Both the point search and clustering methods are optimized using parallel processing techniques to handle large or complex models efficiently. By distributing the workload across multiple threads, the processing time is drastically reduced, making the support generation process viable even for high-resolution models. In this paper we increase speed. Parallel processing significantly reduces the time required for support generation. For highly complex models, the process completes in 23 to 30 seconds on average, compared to several minutes using traditional sequential methods. This makes it feasible to handle intricate geometries without sacrificing speed. As the number of critical points increases with mesh complexity, the method scales efficiently. Tests with dental and industrial models have shown that parallelization improves performance by up to 40%, particularly for meshes with more than 100,000 vertices.

When Point Search and Clustering are integrated, the integration of the point search and clustering methods forms the core of the support structure generation process. The point search identifies critical areas of the mesh that require reinforcement, while the clustering method optimizes the placement of support elements by grouping these points. Combined Error Reduction and Efficiency: When using both methods, error rates in support placement drop by 42%, while the material usage is reduced by an average of 30%. Furthermore, the combined approach completes in less than 30 seconds for even the most complex models, demonstrating the efficiency and effectiveness of the method. Structural analysis of the generated supports shows that they maintain a high load-bearing capacity, with deformation remaining below 1% under typical stress conditions. This ensures that the support structures are both efficient in material usage and reliable during the printing process. In Fig. 2, we tested our proposed method in two dental 3D objects. It is obvious show that our proposed method can clusters meshes and generate cluster center. Fig. 3 illustrates a comparison between support structures applied to a dental 3D object using two different methods. (a) Manual Support Generation: In this subfigure, the support structures were manually created by human operators. This method relies on human expertise to place supports strategically, ensuring the object's stability during the printing process. The manually generated supports are visible as structural elements placed under critical overhanging areas of the dental object. (b) Automated Support Generation: In this subfigure, the support structures were generated automatically using the proposed method. The algorithm strategically places supports without human intervention, optimizing both the quantity and placement of supports to enhance the efficiency and quality of the printing process. The automated supports appear similar to the manual ones but are designed to minimize material use and maximize structural integrity. This comparison highlights the differences in support placement and structure between human-generated and algorithmically generated supports, showcasing the potential efficiency and precision of the proposed automated method.



(a) (b)

Fig. 2. The results of the proposed method in two 3D models (Dental 3D object).



(a) (b)

Fig. 3. A dental 3D object is used to test our proposed method: (a) support structures generated manually by human intervention, and (b) support structures generated automatically by the proposed method.

V. CONCLUSION

This study demonstrates the effectiveness of an AI-driven framework for optimizing support structure generation in 3D printing, specifically tailored for dental applications. By automating key aspects of the printing process—such as object orientation and support generation—our proposed method reduces manual intervention, minimizes material usage, and enhances print quality. The results reveal that AI-generated supports not only streamline the workflow but also maintain structural integrity, leading to higher efficiency and precision compared to traditional methods. These findings underscore the potential of integrating AI into digital dentistry, contributing to more scalable and cost-effective 3D printing solutions. Future work may involve further refining the algorithm for even greater customization across diverse medical and dental applications, broadening the impact of this innovative approach in the healthcare industry.

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