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Informing Architecture with Generated 3D Solid Models

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Abstract

Material data, including interior configurations and faces, is called a 3D solid material. In the past, creating 3D solid materials, especially stochastic ones with a high degree of randomness, was a time-consuming and expensive process. However, machine learning (ML) advancements have made it easier to create such models. Designers can now use microstructural data of materials to create 3D solid models and incorporate material knowledge into the design process. This paper introduces the Leaf Tower project, which explores ways of informing the structural layout of a tower design through 3D solid material models. Specifically, the project uses an ML-based method called Encoding Deep Convolutional Generative Adversarial Network (EDCGAN) to create a non-existing material model from a close-up image of a leaf. Leaves are typically flat, and their vein structures are essentially anisotropic. EDCGANs trained with a close-up leaf image can generate material blocks resembling leaves, transforming 2D images into 3D blocks. Once a EDCGAN is trained to generate a leaf, it learns how to distribute the paths of veins, which is essential for efficiently dispensing water and other resources throughout the leaf surface, known as leaf venation. These basic leaf functions are repeated layer by layer throughout the synthetic material block. The resulting block demonstrates a gradual change and an adequate leaf pattern on every level. Hence, the generated material block extends the logic of a leaf vein system into the three-dimensional space. The process synthesises a grid originating from the leaf structure, which is gradually changing on the vertical axis. Overall, it creates a geometry that is structurally stable and evenly divided. This project adapts the listed qualities of the leaf block into architectural design, particularly an office tower design, by using the divisions and pockets originating from the leaf veins as structural elements and constraints to planning layout.

Keywords: Material Synthesis, Machine Learning, Structural Design, 3D Solid Material, Meta-materials, EDCGAN

1. Introduction

Material data which includes the interior configurations along with the faces is called a 3D solid material. Traditionally, natural heterogeneous materials are challenging to regenerate as computational models due to their complexity [1]. This is due to their composition including several types of elements with different densities and distribution, which are mainly related to the events that occurred during their emergence, making every sample unique [2]. Conventionally, the generation of 3D solid material models could be done by either through a non-penetrable interior scanning of the actual material, or computational estimation using an algorithmic process. The advancements in ML have introduced various directions for creating 3D solid material models. Image-enhancement algorithms can be applied to improve scanned data quality. ML algorithms can efficiently and accurately generate solid materials models [3] [4] [5].

Materials have always been one of the essential elements of design. Liu and Lim have created a detailed list of seven design elements, which include joint, detail, material, object, structure, construction, and interaction [6]. Another list created by Oxman includes form, structure, material, fabrication, and construction [7]. Architects and designers can now incorporate microstructural data of materials into the design process with the availability of 3D solid high-resolution material information. The potential impacts of widely available 3D solid high-resolution material models in architecture are unknown. Possible directions where the new data will change the way things are in the built environment include increased accuracy in simulations, visually more consistent results in computer-generated images of spaces, new opportunities to maximise the consolidated intelligence of materials, therefore increasing material efficiency, and finally, creating new opportunities for meta-material generation [8] [9].

My previous research presents a new approach to generating natural stochastic material's interior structures as computational models, using ML algorithms and giving a minimum amount of input data to create blocks consistent with the original input [10]. In this paper, I use the same method to analyse a given exemplar to synthesise similar 3D solid models while translating 2D data as a seed into 3D data to develop material blocks. The given exemplar is a close-up leaf image. Therefore, the method generates material blocks that are never 3D in real life. This paper showcases the leaf block, which extends the logic of a leaf vein system into the three-dimensional space. Overall, it intends to shed light on the significance of the emergence of a new type of data - 3D solid high-resolution material models - for concept design. It also demonstrates the creative use of this data to inform the design.

The Leaf Tower project proposes to generate a structural concept design using 3D solid high-resolution material models to explore the new frontiers that could emerge with the help of this new data. It proposes to adapt the distribution of material and its microstructure from a micro-scale to a macro scale. The project uses the 3D solid material model creatively while informing the structural layout and architectural design, particularly an office tower design, by using the divisions and pockets originating from the leaf veins as structural elements and constraints to planning the layout.

2. Literature Review

Incorporating detailed information regarding materials can refine environmental calculations by faithfully representing materials in simulations. Digital twins are computer-generated replicas of real-world objects that facilitate analysis, development, and improvement [11]. The generated solid materials are digital twins of input data materials. Improving the overall accuracy of digital twins can increase simulation accuracy [8] [12]. Finite element analysis (FEA), a numerical approach used to resolve physics problems, are too simplistic for materials with unpredictable structures, such as marble and timber [13]. Most commercial software contains a catalogue of materials with average properties. However, incorporating new data can refine environmental calculations by accurately representing materials in simulations.

Another possible direction in which the new data will change how things are in the built environment is to use ML-based solid texture tools as meta-material generators [9]. Metamaterials inspired by natural structures such as bone tissues are a well-studied area [14] [15] [16] [17]. ML tools can enable metamaterial generation inspired by natural heterogeneous materials [18] [19] [20] [21].

The Leaf Tower Project analyses the small-scale material information—a 3D solid material model—on a larger scale. Deriving structural concepts by taking inspiration from material behaviour is a widely recognized approach with historical contributors such as Antonio Gaudi and his hanging models to solve masonry arches, Heinz Isler and his works exploring shell design strategies with hanging clothes and membranes, and Frei Otto with his model-based experimentations using various types of materials [22] [23] [24]. Kostas Terzidis refers to materials as data while pointing at the grains of timber as a natural code and information [25]. The data can inform design directly at the same scale or be interpreted at different scales as information models.

Adapting the implicit logic of leaves into architecture by focusing on the distribution of the veins, which is essential for efficiently dispensing water and other resources throughout the leaf surface, known as leaf venation, can be categorised under biomimicry. Biomimicry refers to deriving inspiration from nature in terms of aesthetics, structure and performance [26]. Some examples of bio-inspired projects are stadium structures based on the human femur and kinetic facades inspired by flower shapes [27] [28]

[29]. Biomimicry often requires a transition in scale where the proportions and relationships of natural structures are considered instead of their actual sizes [30]. An example of bio-inspired architecture is a pavilion design made by the University of California Studio 1. It showcases an example of translating the structural logic of plants to a larger scale while aiming to solve the challenge of gaining rigidity and strength from malleable and flexible parts [31]. Similarly, in the Leaf Tower Project, the grid originating from the leaf structure creates the planning layout of the office tower.

ML has been used extensively in generative image modelling. Algorithms like generative adversarial networks (GANs), variational inference and autoregressive are among the well-known techniques [32] [33] [34]. This paper presents a detailed example of how ML can be used as a tool for conceptual design. It utilises GANs to create material blocks that resemble leaves. These materials are then used as a guide for structural design. The Leaf Tower is proposed to be a concrete frame structure. When designing concrete frame structures, it is crucial to carefully consider the layout of the beam system since it plays a vital role in supporting and transmitting vertical loads [35]. There have been several studies on concrete beam layout design to be supported by ML algorithms [36]. GANs have been widely used for concept design and are considered highly effective in generating conceptual images [37] [38]. Furthermore, GANs have been applied to many areas in the built environment for generative tasks, from floor plan generation to urban planning [39] [40] [41].

3. Approach

Previous research presented a new approach to generating material blocks using ML algorithms and giving a minimum amount of input data to create blocks consistent with the original input [10]. It introduced a new system called Encoding Deep Convolutional Generative Adversarial Network (EDCGAN) to create a material cube from a close-up image.

First presented in a paper in 2014 by Goodfellow et al., GANs are based on two networks working against each other: a generator and a discriminator [42]. The first network learns to generate images, and the second learns to detect the mistakes in these images. Therefore, after sufficient training, the results of the generator begin to pass the realness check of the discriminator. Hence, the generator becomes better at creating images of increasing verisimilitude. Based on this structure, a sufficiently trained generator takes noise images as an input and creates images similar to the input dataset as an output. There are many variations of the initial GANs research. This paper focuses on an unsupervised version of GANs using a convolutional neural network (CNN) architecture called DCGAN [43]. In detail, the proposed method of EDCGAN includes two DCGANs working together. The first DCGAN is trained with the initial dataset, while each time the generator section of the network creates an image, the discriminator rates the result based on its success. This rating is then transferred back to the generator. Eventually, this process leads to a generative network that knows how to create a believable image from an input of noise. Once the training is complete, to create the dataset of the second DCGAN, the noise data and its associated tiles are recorded. The second DCGAN is trained with the new dataset to turn generated tiles into noise. After training, both DCGANs are combined in a reversed order, with second as first and first as second. The consequence is a combined system that can turn any tile into noise, and from that noise, a tile is generated.

This method analyses a given exemplar for an ML algorithm to learn to create similar 3D solid textures, consistent with the original input. Specifically, it aims to generate a material block from a leaf image while maintaining consistency with the original input. Leaves are typically flat, and their vein structures are largely anisotropic. If the system is given a close-up image of a leaf to learn from, it can generate material blocks that resemble leaves, transforming 2D images into 3D blocks. Figure 1 illustrates the original leaf image that was used as an input to create a dataset for the algorithm.

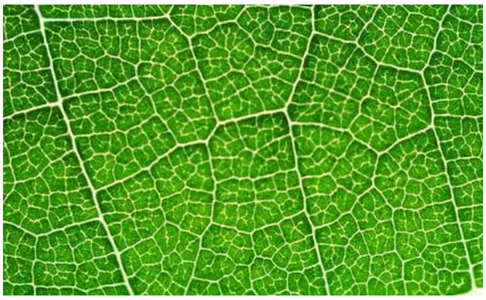

Figure 1: Close-up leaf image.

To create a leaf block, the first step is to train a DCGAN with tiles extracted from an exemplar. The model acquires the ability to reproduce the implicit logic of the original image. By training the model to generate a leaf, it learns how to distribute the paths of veins evenly to ensure the efficient dispensing of water and other resources across the leaf surface, known as leaf venation. The output of the algorithm is a single layer of the material block in Z-axis. By repeating the same process layer by layer, the synthetic material block can be created. The generic process of turning a leaf image into a 3D material block consists of creating the dataset of tiles, training the combined system of DCGANs, generating a sequence of leaf images, and creating a 3D material block from the sequence. The resulting block demonstrates a gradual change and an adequate leaf pattern on every level. Hence, the generated material block extends the logic of a leaf vein system into the three-dimensional space.

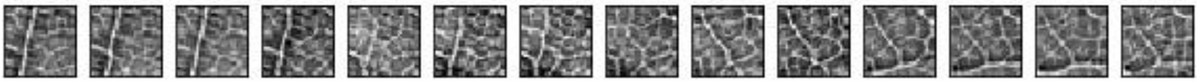

Figure 2: The sequence of a leaf block generated with EDCGAN.

As the algorithm create a 3D leaf block using the original leaf image, the veins of the leaf, evenly distributing resources including water, continue vertically and change gradually, creating a partition system on a non-standard and non-uniform grid, as shown in Figure 2. The resulting model is generated using the pixel-based technique. The greyscale leaf images are separated into two groups based on a greyscale threshold value of 90. Lighter areas, which are the representation of the leaf veins, are selected to include in the final model. Figure 3 shows the rendering of the leaf block.

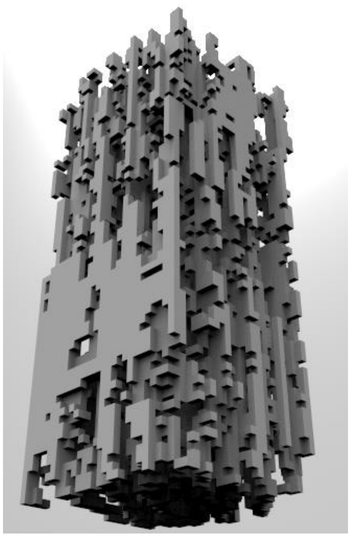

Figure 3: The leaf block generated using EDCGANs.

A 3D printed version of this model is produced to analyse the block in terms of its vertical connectivity and continuity, as shown in Figure 4. The result proves that the final geometry works as a single entity. Hence, the algorithm accomplishes to synthesise a connected model with no size restrictions on the Z axis. The pixels above the greyscale value of 90 are connected to the next level at each layer, resulting in an uninterrupted and continuous model. Moreover, the grid originating from the leaf structure is gradually changing on the vertical axis. The block is stable and stands on its own. Figure 5 displays cross-sections of the block and different views of the material in a cubic shape.

Figure 4: The 3D-printed model of the generated leaf block.

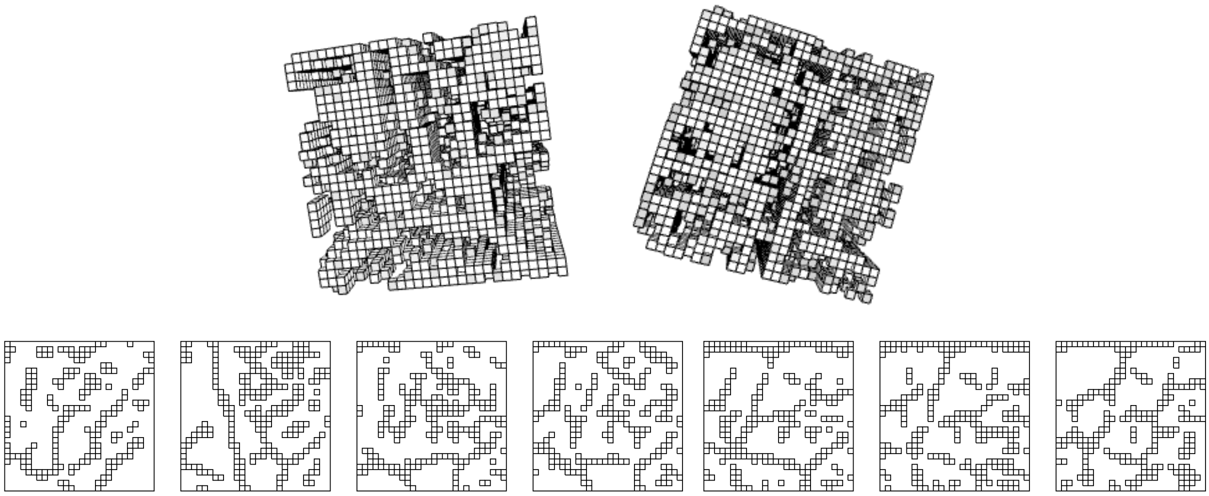

Figure 5: Cross-sections and different views of the block generated using EDCGAN model.

4. Visualisation and Discussion

Leaves aim to distribute an equal amount of water throughout their surface while staying flat and wide to increase what they absorb from the sun's emission. By training a EDCGAN, material blocks with leaf-like qualities in every slice can be created. This method creates a geometry that is structurally stable and evenly divided. This section presents an architectural project where the solid material data informs the structural layout for a tower design. The tower adapts the listed qualities of a leaf into architecture at a larger scale, by using the divisions and pockets originating from the leaf images as structural elements and constraints to planning layout. Figure 6 demonstrates the design process starting from choosing a leaf image, to creating a dataset from the image, training EDCGAN to create a material block that repeats the leaf logic at every level.

The paper uses the pixelated structural layout produced by the EDCGAN model as an architectural guide, leaving the tower's structure open to interpretation. While translating the concept into a structure, possible directions include using the pattern as a grid for beams and columns or introducing a combination of columns with shear concrete walls. In the plans, pixels are represented as boxes and proposed as prefabricated structural elements to function as either a concrete shear wall or a column.

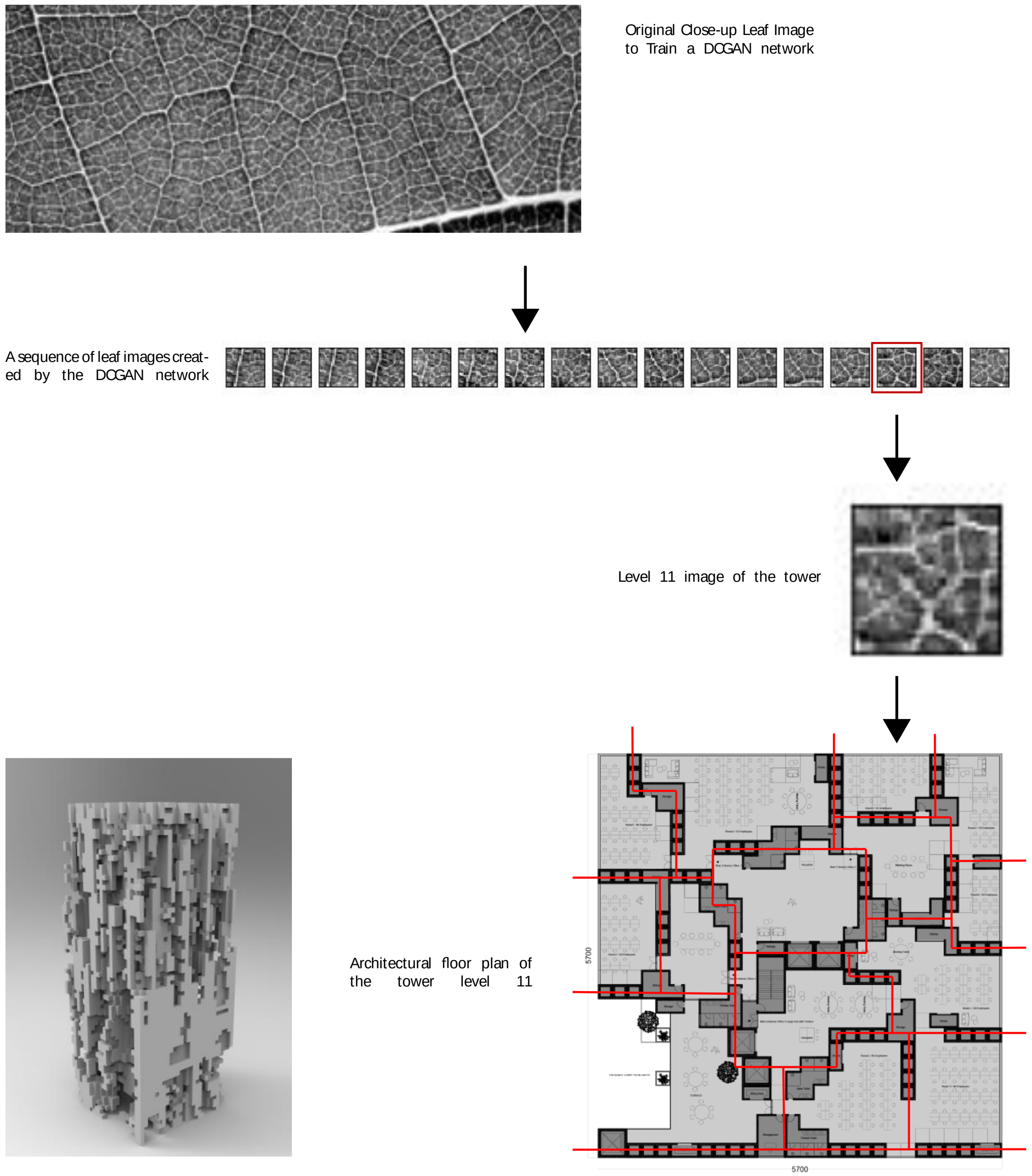

Figure 6: A diagram explaining the design process of the Leaf Tower Project.

The proposal is an office tower that utilises the generated geometry with embedded leaf logic. The tower consists of pockets of space on each floor, used as office spaces, conference rooms, lobby spaces, etc. In detail, the first three floors are dedicated to lobby and conference hall facilities. Each conference room occupies a pocket. There are 14 pockets on the ground floor, and some of these pockets are used as outside spaces. Following the first three floors, the tower continues with office spaces until the top. On average, there are 14 pockets per floor and 34 floors.

The lobby space is divided between interior and exterior and is located at the bottom of a cut-out, which continues on the west façade as the tower rises. This cut-out ends with a private terrace on the 11th floor for office use. There are various small pockets of green spaces in addition to the vertical gardens attached to the solid sections of the façade. Therefore, green areas can be seen in different sections of this tower. Overall, the continuing structure originating from leaves changes as the tower rises. This structure bears the load of the building and hides all the side functions concerning the main programme. Supporting functions including toilets, storage, kitchens, print areas etc. are proposed to be prefabricated modules to be installed on site. There are 13 different shapes of supporting function modules. Figure 7 demonstrate the street level plan layout showing the lobby area and a generic plan layout of office spaces. Finally, Figure 8 show renders of the tower in perspective.

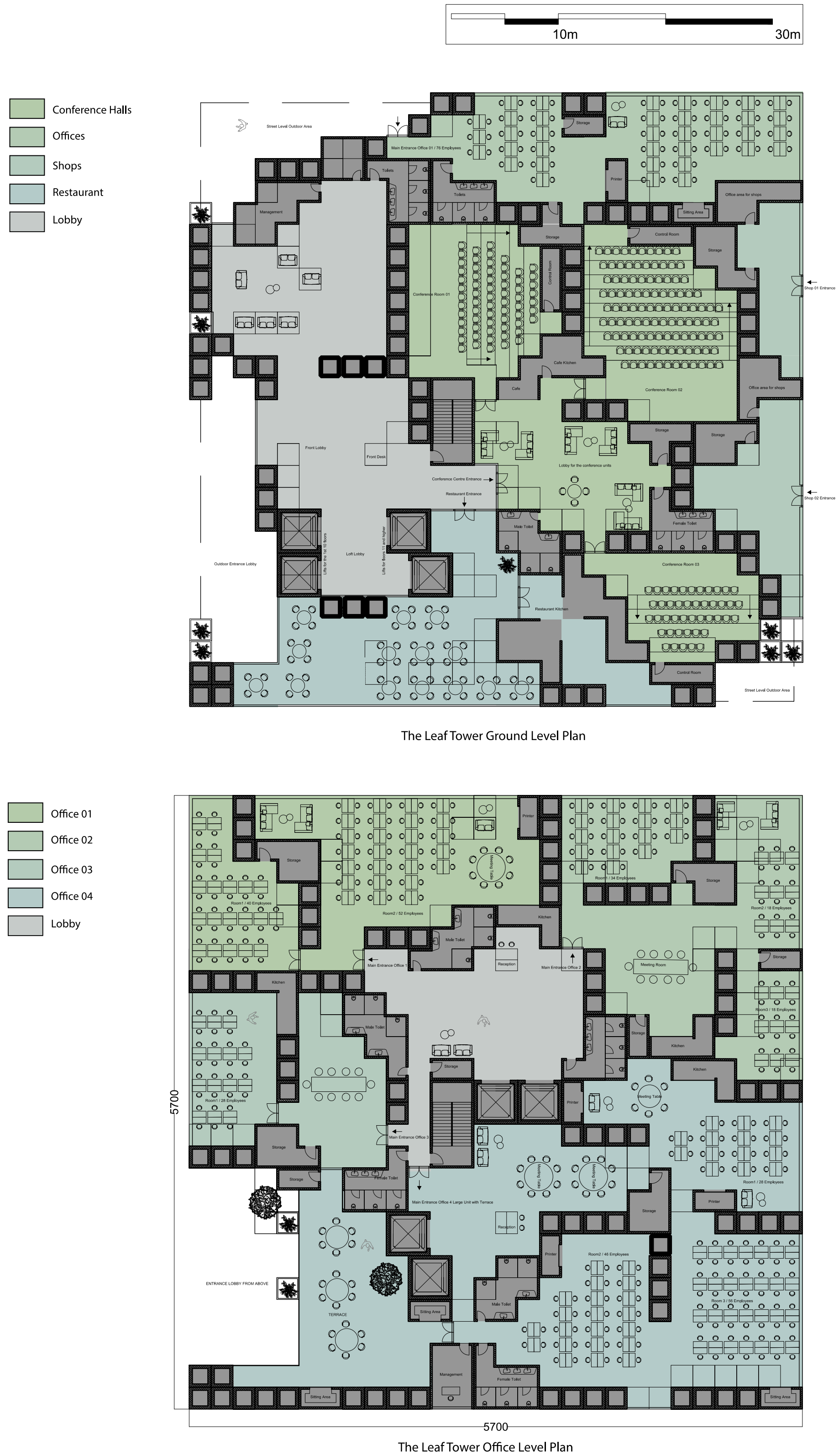

Figure 7: The Leaf Tower Project ground plan and a generic office-level plan.

Figure 8: The Leaf Tower Project render.

5. Conclusion

The field of architecture is poised to enter a new and exciting phase with the recent advancements in ML. The integration of ML into the design process has the potential to revolutionize the way architects approach their work. Material information has already become the driving force behind a new design language in the leading architectural schools over the past few years. This development can significantly enhance the efficiency, accuracy, and creativity of architectural design beyond aesthetics. This article discusses the new availability of 3D solid material models and possible directions in which they will change the way things are in the architecture world, such as increased simulation accuracy, increased consistency in computer-generated images, increased material efficiency, and new opportunities for meta-material generation. It presents the potential of a new design concept triggered by the generation and easy accessibility of 3D solid material models while shifting the traditional design paradigm from fitting a material into a design to fitting a design into a material.

While describing a method for informing concept design with the new material data, the paper described a workflow that starts with choosing a 2D image with underlying material logic. The 2D logic is then synthesised in 3D space, and a structural diagram inspired by the material is created. This diagram is used to develop a structural concept and the spaces surrounding this structure. The tower's design is inspired by the microstructure and material distribution within leaves. The leaf block informs the structural layout and architectural design of the project, using the divisions and pockets originating from the leaf veins as structural elements and constraints in planning the layout. For future studies, the workflow of the paper can be used to explore other non-existing materials. The structural performances of these materials can be calculated and compared to each other. Additional structural analysis can be carried out to compare the proposal with a concrete frame structure of the same capacity. The amount of materials used in this structure can be compared to that of traditional structures.

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