ML and Robotics for Generating and Fabricating Compositions with Discrete Elements

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Architectural construction methods have always included modularity, an important part of the masonry technique, composed of smaller units that are diverse. The emergence of irregular/non-conventional forms and units arising from this diversity highlights the challenge of assembling precision. As existing materials, salvage materials that are accumulated by the increased number of demolitions could be convenient sources for generating these kinds of structures that serve the concept of circularity. That area is open to contributions since there is a research gap so far. The present study utilizes stereotomy, which is a technique of combining individual units by cutting and carving to avoid gaps. Moreover, within the scope of the circular approach, it is aimed to minimize the amount of cutting and carving to decrease the waste. The combination of discrete irregular structural modules will be generated by the guidance of decision trees, convolutional neural networks (CNN), and constrained K-means models. These models are utilized to classify and cluster the existing patterns, which are masonry wall images containing features of stereotomy and stacking as an emergence point to provide stereotomic bonds between the modules. A dataset of stone masonry wall images was created, leveraging the wide variety of stone forms and combinations. Trainings of the models are done with the features extracted from these images, which resulted in accuracy rates varying between 0.63 and 0.79, leading to an output pattern proposed for a set of objects that will be assembled through robotic fabrication. This study shows that it is possible to generate and fabricate combinations for irregular elements regarding stereotomy by implementing machine learning and robotics.

Keywords: *Irregular Elements, Stereotomy, Decision Tree, CNN, Robotics.*

INTRODUCTION

Within the context of architectural construction techniques, modularity plays a significant role, specifically for masonry works. The modules comprising a masonry structure could vary from regular/conventional to irregular/non-conventional. The change in the shapes of the materials has the potential to lead to the problem of precision for the modular structures. From different types of approaches, the technique of stereotomy, which is an extensive area, is chosen to be used for overcoming this problem. Materials with irregular shapes can be found in existing materials that could be salvaged materials, which encourages circularity. It is hard to manage a composition with salvage materials since they are mainly composed of irregular elements (Huang et al., 2021). Nevertheless, ML methods are planned to be employed to cope with this problem. Following the system proposed for the composition stage, the output structure could be fabricated by a robot arm.

To minimize the waste materials for the construction stage, the cutting and carving operations that are part of stereotomic applications are planned to be avoided. The materials will be put together as they are, according to an output pattern placement based on predictions. This study hypothesizes that ML models are beneficial to generate new combinations of discrete elements, which are salvage materials in this case, with the use of stereotomic principles, and these can be fabricated utilizing robotics. Masonry wall images gathered from the internet are used as the base of the dataset since they offer various types of shapes and their relations in a whole composition. The background research is completed in the fields of stereotomy, modularity, masonry, and related ML and robotics applications to guide the study.

LITERATURE REVIEW

Singular units can be combined to create a structure in the concept of modularity, in contrast with holistic production methods. Even complex structures can be assembled with this technique, which could cause different force distributions among the modules that should be considered in the design stage (Ivaniuk et al., 2022). In the scope of experimental architecture, pavilions and installations have started to be built with modular units that have significant examples such as the BlobWall and Alessi Tea & Coffee Towers done by Greg Lynn (M Rocker, 2006; Lynn, 2009).

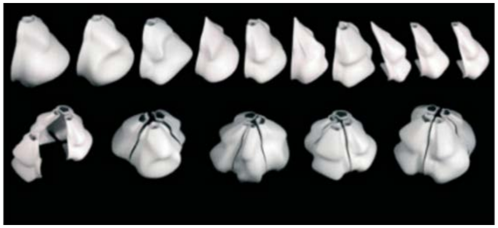

Figure 1
Non-conventional Modules of Alessi Tea & Coffee Towers (M Rocker, 2006)

Composing modularity and automation could enhance the stability of the structure as well as accelerate the process (Graur, 2020). Stereotomy is applied with the logic of modularity by the assembly of individual units fabricated through processes like wire-cutting, waterjet, and CNC milling according to the properties of the material (Fernando, 2019). Along with technological development, modularity, computerization, and automation in fabrication are being widely applied in masonry structures (Varela & Sousa, 2019). This is viable by the utilization of robotic arms, drones, and so on, to assemble the structure with the benefit of computational models having the information of the modules and the end structure (Paris et al., 2023). Masonry manuals could be the guidance for the agents; however, the information should be adjusted; hence, they were written for the people (Liu & Napp, 2023). An arrangement should be created to have a self-standing structure for these kinds of constructions with the help of planning programs by organizing the structural elements in compliance with their properties, like material, shape, and size (Ko & Hsieh, 2023; Thangavelu et al., 2018).

In the light of masonry and modularity, stereotomy, whose meaning comes from combining the words "solid" and "cut", is a way of creating the composition by cutting and firmly stacking the solids as Fallacara & Barberio (2018) experimented. Tessellations could be the advent point of stereotomy, which turns into a self-supporting structure (Diles, 2018). Stereotomy reveals itself in Cyclopean walls called megaliths, which are mostly built as dry-stacked, with the well-known example of Machu Picchu in Cusco with the logic of putting the blocks one by one in the construction stage, giving importance to the sequence to overcome the problem of irregular bonds (Clifford & McGee, 2018; Šaravanja, Oreč, & Kopilaš, 2023; Protzen, 1985).

Stereotomy in architecture is improved through the implementation of computational methods, resulting in intricate structures arising from the birth of Stereotomy 2.0, which is interpreted in the works of Fallacara & Barberio, 2018; Fallacara & Stigliano, 2012; Varela & Sousa, 2016. De Azambuja Varela and Meritt (2016) experimented with stereotomy to build a cork vault by using 5-axis CNC and waterjet cutters by tesselating the surface of their design. Different types of materials are used within this context, rather than stone blocks containing lightweight materials; one of the examples can be seen in Figure 2 by Diles (2018).

Figure 2
Sectional Prototype of Plasticity Pavilion (Diles, 2018)

Another aspect of this study is to reuse salvage materials that reduce the carbon footprint and ensure circularity by means of sustainability. The studies that use sustainable materials are increasing with the awareness of the designers, including salvage materials. One example that also considers the combination of elements is the European Council Building in Brussels, designed by Samyn and Partners. They integrated a facade system, which can be seen in Figure 3, composed of old windows into their designs (Gorgolewski, 2018).

Figure 3
European Council Building, Brussels (Rojas, 2016)

One of the reasons why reclaimed materials are not preferred extensively is that their irregularity complicates the creation of a composition (Witt, 2022). Creating an inventory of these materials would make the process easier. One of the studies uses irregular reclaimed concrete masonry blocks for creating structures by creating an inventory of their scanned models that can be seen in Figure 4. Yet, this study only introduces a system of matching 2 pieces that are assessed via their proximity to each other (Marshall & Lausanne, 2024).

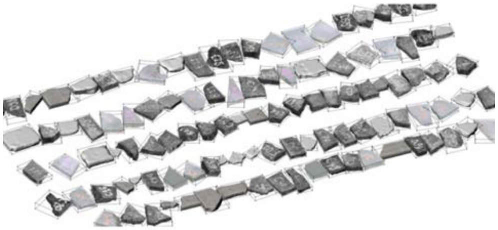

Figure 4
Training Data (Marshall & Lausanne, 2024)

Along with computing methods, artificial intelligence, which has a wide application area, can be implemented to solve such a problem. The methods that are created with both machine learning and deep learning strategies, developed for packing and stacking, can be useful for combining pieces. Together with AI models, robotics can be utilized in the manufacturing stage with a step-by-step approach, since the system could be unstable with irregular object placement. Several studies work on dry stacking irregular objects, some of them done by Wermelinger et al. (2018), Paris et al. (2023), Zhou et al. (2023), and Menezes et al. (2021); Liu (2023) published her dissertation specifically on this topic.

METHODOLOGY

As a part of research in progress, it is aimed to build a configuration from discrete structural members/salvage materials concerning the stereotomic bonds between elements that can be present in masonry structures that are selected for the main dataset by machine learning, then experimenting with this configuration by a robot arm in a simulation environment based on a pipeline presented below.

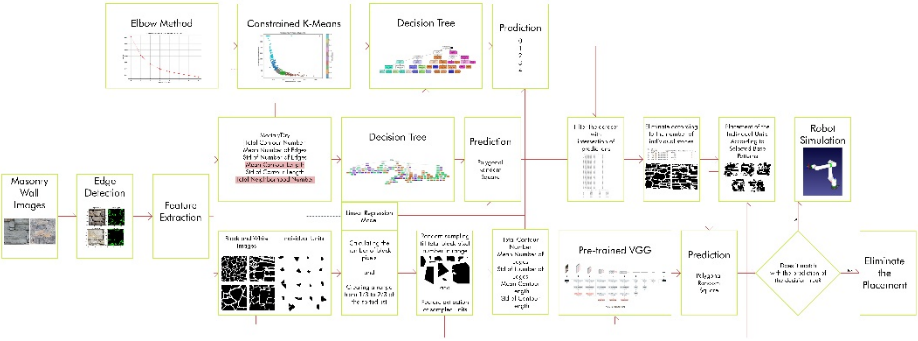

Figure 5
The Research Pipeline

As a beginning point, the dataset is created by scraping images of masonry wall patterns from the internet; later, these images are preprocessed to have consistency, and all of them are the size of 256x256 pixels (Figure 6). The reason for choosing masonry wall images as the dataset is that they serve a variety of shapes and connection possibilities.

Figure 6
Data Collection

After gathering the images, to comprehend the masonry walls, an edge detection algorithm depending on adaptive thresholding, produced by using the OpenCV library, is applied with a contour approximation proposed by Douglas and Peucker (1973) to reduce the vertices. The images that can be read by this algorithm compose the actual dataset (Figure 7)

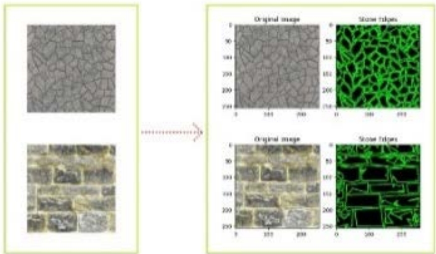

Figure 7
Edge Detection

The contours obtained from the edge detection are the main sources of information that could be derived from the patterns. To reach this information, 2 types of feature extraction are performed on these contours. The first approach is to get geometrical properties, which can reveal the interrelations of the pattern in terms of its integrals, by deriving the information of total contour number, the mean number of edges, the standard deviation of edges, the mean contour length, and the standard deviation of contour length, and total neighborhood number. Additionally, the information on Mortar/Dry is added to this data. The second approach is to use the DXF files that are linked to the edge detection to create black-and-white images of the patterns that reveal the visual comprehension of the patterns. With these feature extractions, the models that will be used will be able to grasp the essence of stereotomic bonds within the existing patterns.

After getting these feature extractions, the first decision tree classifier is trained with a CSV file composed of initial features with the labeling of random rubble, square rubble, and polygonal rubble which are derived from a wide range of categories, especially from the work of Szabó, Funari, & Lourenço (2023), that are reduced due to a limited amount of data (figure 8).

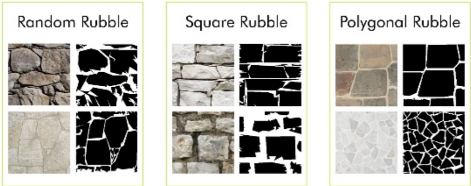

Figure 8
Examples from Labels

The CSV file has 393 rows of data that are used with a 70-30 train-test split for training the decision tree model that is based on a tree model answering questions at each node. The measure of randomness is set to Gini impurity for this training, resulting in an accuracy level of 0.66. The classification report (Table 1) shows that the model generalized the data well, even though there is a slight imbalance.

Table 1
Classification Report

	precision	recall	f1-score	support
Polygonal Rubble	0.67	0.65	0.66	34
Random Rubble	0.61	0.72	0.66	43
Square Rubble	0.74	0.61	0.67	41
accuracy			0.66	118
macro avg	0.67	0.66	0.66	118
weighted avg	0.67	0.66	0.66	118

In parallel with this model, to understand the distribution of the patterns in the dataset, an unsupervised model is selected on the side to cluster the dataset based on the first feature extraction. The selected model for this task is a K-means model, which is trained with the features of mean contour length and total contour number that are determined according to the pair plotting. Due to uneven distribution with the K-means model, Constrained K-means (Bradley et al., 2000) is selected to proceed with to ensure a similar amount of data for each cluster, whose number is determined as 5 in compliance with the elbow method.

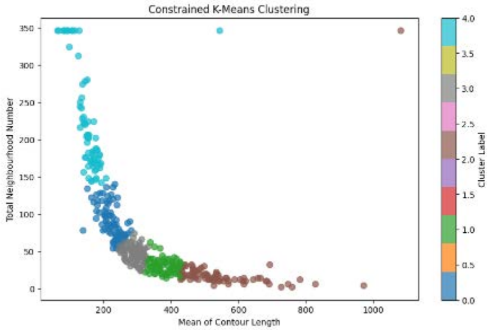

Figure 9
Constrained K-means Clustering Distribution

The data is distributed as 83 patterns for cluster 0, 80 patterns for cluster 1, 73 patterns for cluster 2, 83 patterns for cluster 3, and 73 patterns for cluster 4; examples of them can be seen in the following figure.

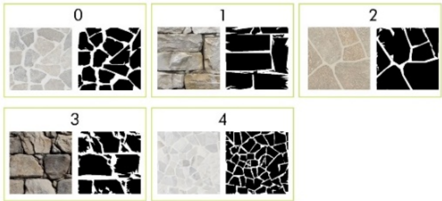

Figure 10
Examples from Clusters

To have a prediction regarding the remaining features based on this clustering, another decision tree is trained. The accuracy of this model is 0.77, which could give consistent predictions (Table 2).

	precision	recall	f1-score	support
0	0.79	0.88	0.83	25
1	0.62	0.67	0.64	24
2	0.93	0.59	0.72	22
3	0.69	0.80	0.74	25
4	0.95	0.91	0.93	22
accuracy			0.77	118
macro avg	0.79	0.77	0.77	118
weighted avg	0.79	0.77	0.77	118

Table 2
Classification Report

The second feature extraction method is used to assist the decision tree model. Since these are image files, convolutional neural networks (CNN), particularly VGG-16, are selected as the model. The pre-trained model from Tensorflow Keras is used for the training. Since the labels are different from the pre-trained model, the top fully connected layers of the model are excluded and replaced with three. After 10 epochs of training, the model reached an accuracy of 0.79 (Table 3).

	precision	recall	f1-score	support
polygonal	0.74	0.92	0.82	25
random	0.71	0.84	0.77	44
square	0.97	0.68	0.80	47
accuracy			0.79	116
macro avg	0.81	0.81	0.80	116
weighted avg	0.82	0.79	0.79	116

Table 3
Classification Report

Another important step followed in the pipeline is that random sampling is done through the data of separated individual elements that are used instead of a possible set of salvage materials. Since the sizes of the images agree with each other, random sampling is done based on the black pixel count. The sampling stops when the number of black pixels is in the range of 46948-52742 pixels, which is derived from the original dataset. Different samplings can be gathered by changing the random seed. For example, the figure shows one of the samplings, that is, when the random seed is 6.

Figure 11
Selected Individual Pieces for Random Seed = 6

Superposition of the predictions, from the trained decision trees based on the features of the sampled pieces, is used to narrow down the dataset into the most possible patterns. For example, the given sampling is predicted as random rubble for the first decision tree and cluster 0 for the second decision tree. The dataset is narrowed down to the ones that are both random rubble and cluster 0, with the final narrowing to pick the ones with 23 pieces, to be the same as the number of sampled pieces.

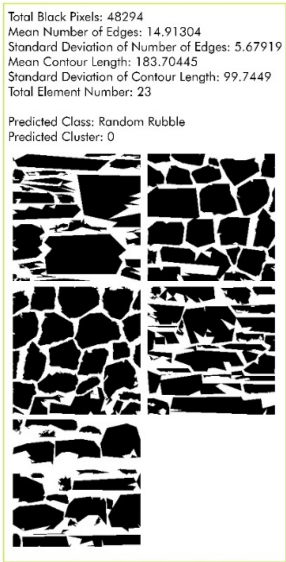

Figure 12
Predictions and the Possible Base Pattern

The most important part of this study is to manage the placement to derive the output patterns. In order to achieve that, the sampled pieces are placed into the selected possible base patterns with an algorithm that matches the patterns with an algorithm that matches the individual pieces and the pieces in the patterns according to their sizes. The logic is to place starting from the largest pieces to the smallest pieces. It initially places the piece as it is; if there is an overlap, it tries to eliminate it by rotation first, then a small translation. The placement options for the selected example can be seen below.

Figure 13
Placement of the examples when random seed = 6

After acquiring these placements, another prediction is made with the trained VGG16 model to verify the label with the previous decision tree model. It shows whether the stereotomic bonds are established precisely according to the sampled units. The placement from the earlier example is given to the model for prediction; all five of them resulted in the correct label, which is random rubble. Hence, these placements are eligible for production.

Table 4
Placement evaluation

Filename	Feature Distance	Coverage Distance
1	2836.970923	-0.091170552
2	2320.155301	-0.012119293
3	2010.473435	-0.036952534
4	2525.253896	-0.023114187
5	2282.1119	-0.195706765

Besides, the produced placements are evaluated through the calculation of feature distance, which includes the features of edge number, contour length, area, and aspect ratios of the contours, and the distance between the coverage ratio of the original pattern and the produced patterns (Table 4). The feature distances have approximate values, yet the 3rd one has the lowest value, and the first one has the highest. In terms of the distance between the covered area is the least for the 2nd placement while it is the most for the 5th placement. Considering the correlation of these metrics. The second placement seems to be the most feasible option.

After getting the eligible placements, the first placement option is selected to perform a robot simulation that is implemented in RoboDK using the Python API. The selected individual pieces are extruded inside Rhino and exported in STL format, which is suitable for importing into the RoboDK environment. The reason for extruding the pieces is that the proposed method deals with planar configurations. After that, these pieces are imported by using a grid to eliminate collision between them, which is also used to define the pick locations (Figure 14).

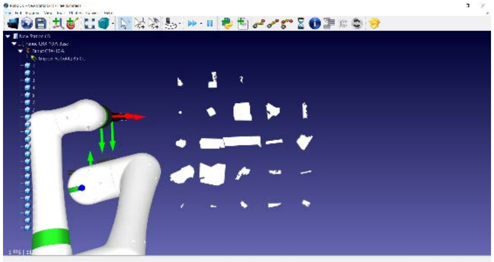

Figure 14
Imported pieces into the RoboDK environment

Then, the DXF file that contains the contours of the placement is read through the Python environment. Its location information is processed to have the final placement within the robot's reach. The individual pieces are matched to the contours by their base areas. After matching, the place positions are defined according to the DXF location. The simulation of pick and place is performed using the defined locations (Figure 15).

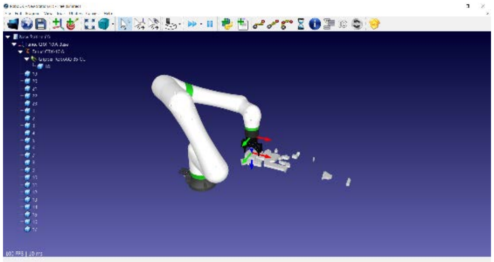

Figure 15
Pick and place simulation

The result of the simulation, which is shown below, demonstrates that the overall placement is achieved despite small misalignments.

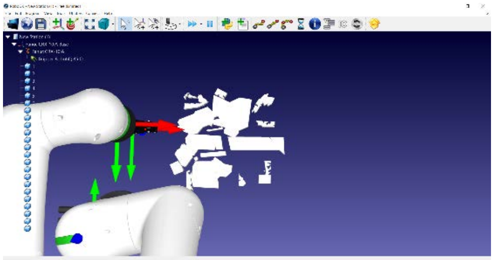

Figure 16
Result of simulation

RESULTS AND DISCUSSION
Ultimately, existing images of masonry could be a leading point for ensuring stereotomic bonds between irregular pieces. AI models assist in the process of obtaining base patterns for a set of individual pieces. The study could be extended by increasing the amount of data, which currently consists of 393 images. This approach can increase the prediction ability of the models; besides that, the options can also be increased to find better placements. Some trials fail to match a distinct pattern, and this problem can be overcome with more data. Further, robot simulation is useful to see the assembly stage of proposed placements, and it can be implemented in real life. Hence, cameras or sensors can be integrated into real life to automate the process via RoboDK's Python API. Salvage materials mostly have irregular shapes, so any group of salvage materials can be combined with the approach followed in this study by gathering their edges them.

CONCLUSION
As a result, this proposed system, which is part of a larger study, has achieved consistent results in creating a composition by learning from existing patterns by looking at the metrics used. The assembly phase and the extent of the data are the parts that need further improvement. The most important part is to transfer the performed simulation into the real-world experiment. This stage will enable Human-Machine Interaction. After following these steps, this study can also be broadened to 3D space to solve more complex structures.

NOTES
This work is part of a master's thesis conducted by one of the authors (Solmaz, 2025) within the Building Science program at Middle East Technical University (METU). The dataset is available at: https://github.com/emire-

nr/Masonry-Wall-Images-and-Edge-Detections/tree/main

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