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AI-D. ALGORITHMIC EXPERIMENTS WITH AI TO AID DRAWING

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Abstract

This paper investigates the capabilities of artificial intelligence to support the architectural drawing process through a style transfer experiment. The goal is to transfer Frank Lloyd Wright's drawing style to contemporary photographs, evaluating how the algorithm can replicate the distinctive features of Wright's graphic language. The proposed method explores the potential of AI not only as a technical tool, but also as a creative medium capable of reinterpreting complex styles. The results highlight implications for architectural design, offering new perspectives on the use of AI to innovate visual design and stylistic exploration.

Keywords

Artificial Intelligence, Style Transfer, Architectural Drawing, Representation, Digital Drawing

1. *Introduction*

The present study aims to investigate the potential of artificial intelligence (AI) for architectural design, proposing a novel experimental process that transfers computer-aided design (CAD) into computer-aided drawing. The enthusiasm surrounding this "disruptive technology" is influencing the methods of project and graphic production (Bölek et al., 2023; Brozovsky et al., 2024), but there is an awareness of the increasing loss of control over the relationship between input and output, as well as the replicability and scientific rigour of the process, which remains inherently stochastic. The present study focuses on the field of investigation that regards drawing as the soul of architecture, in a similar manner to the score for music. The studies developed in this field of research led to a deepening of the value and meanings of drawing as product and process (de Rubertis, 1994) warning by the simplistic notions of Pygmalion's deceit, such as the infatuation with the statue he created, which conveys a profound sense of meaninglessness.

Fig. 1: Displaying outputs by using drawings as input in the workfllow.

As a result of both enthusiastic endorsement and condemnation, AI, in a manner reminiscent of Ovid's myth, has the potential to alter our relationship with reality, our understanding of it, and therefore our interpretation of our place in the world (Kissinger et al., 2023). This *techné* demonstrates the capacity to raise ethical (Baldassarre et al., 2024), creative, and practical issues, as it is not merely a tool for automated text or image production. Rather, it is a technology that expands and redefines the creative and exploratory potentialities inherent to AECO sectors. Furthermore, beyond the efficiency of processes (Verganti et al., 2020), it appears that AI extends the boundaries of possibility and imagination (Castro Pena et al., 2021; Ji, 2022). The fundamental issue is that the new messages created by the medium (McLuhan, 1964) transform outcomes and processes, but also objectives themselves.

In the field of architectural drawing, it is interesting to situate AI as an evolution of the algorithmic approach that had revolutionated representation logistics (Filippucci, 2023). Before AI successful, Computational design (Filippucci et al., 2016) have played a pivotal role (Paoletti, 2018) in shaping new conceptualisations in architectural design (Hensel & Menges, 2006; Menges & Ahlquist, 2011; Schumacher, 2009) for informated architecture (Paoletti, 2018). It is ufeful to mark as generative design and AI are both both processes that can be stigmatised in a tripartition of the path between input, processing and output, leading to an authorial and temporal disjunction between the representational act and the produced result (Bianconi & Filippucci, 2019). With the construction of parametric algorithms comes a profound transformation of procedures, goals and results (Bianconi et al., 2024), impacting the canonical approach of verifying solutions (form-checking) towards the search for forms that meet criteria (form-finding), exploration of possible combinations of configurations in the search for 'for the best' solutions (Renner & Ekárt, 2003). AI emphasises such combinatorial search (Taj & Jhanjhi, 2022), offering extraordinarily sophisticated solutions that require fewer input data and elide the construction of the algorithmic process, which is automated in a kind of "black box". In this simplification of processes (Bölek et al., 2023), it extends the architectural scope beyond the functional scopes (Chaillou, 2019): using AI, in a simpler way, it is possible for exemple to come up with arrangements of spaces based on criteria that include not only functional considerations, but also ergonomic, contextual and perceptual requirements (Baroš et al., 2022; Viliunas & Gražulevičiūtė-Vileniškė, 2022), as well as in the digital twin it is learning to understand the behaviour of buildings (seismic, energetic....) to support adaptive processes by improving the ability to predict and optimise operations (Almusaed & Yitmen, 2023).

Basically, AI extends the scope and takes on the great challenge of managing complexity, which has been substantially caused by digitisation itself, with its prolification of information (Forsyth, 1999) and the centrality of images (Castells, 2002).The potential to process massive amounts of data (Iafrate, 2018) and transform it into information is leading to a new industrial revolution (Taj & Jhanjhi, 2022) hat impacts the interpretation of reality, from the city to architecture. A possible emblem of such an approach is the ability of AI to train itself to understand what the pixels of photos represent with the aim of classifying them, which, in the plurality of approaches, methodologies and purposes, is projected to the semantic decomposition of visual complexity into patterns and pattern recognition, as shown for instance by experiments on the construction of maps from photos (Bianconi et al., 2023) or the automatic recognition of architectural styles from images (Cantemir & Kandemir, 2024), which can be linked to the determination of the building's construction period (Sun et al., 2022).

AI is used, also in the field of architecture, in the manipulation of images through style transfers, transforming their visual appearance while leaving the structure or content unchanged, as is the case in the transfer of colours (Ke et al., 2023) or the alteration of graphic identity (Pan et al., 2022), processes that are also applied in the transformation of the stylistic imprint of architectural drawing (Wang et al., 2023). The preponderance of the use of textual prompts should be emphasised (Luo et al., 2023), as well as the need to costumize processes, which, as is the case in generative logics, finds in the nodal representation a preferential path.

AI then proposes itself as an aid to design heuristics, a transmigration of that figurative activity of recomposing images (Husserl, 1960) that takes place in the human mind in creative processes (Arnheim, 1965) and that in the "machine hallucinations" wants to discover suggestions beyond the imaginable (Del Campo, 2022). Thus emerges the full role of AI as *techné*, which becomes an active agent capable of transforming design practice through enhanced thinking, in which human creativity is hybridised with increasingly refined computational capabilities (Harapan et al., 2021). Digital processes impact in the conception and soul of architecture (Brisco et al., 2023; Castro Pena et al., 2021; Chen, Shao, et al., 2023; Jo et al., 2024; Paananen et al., 2023), "from the spoon to the city", in an approach that offers itself as a facilitation of the process of conception and exploration that is inherent in the immediate visualisation of multiple solutions. The complexity of the neural networks that substantiate machine learning is hidden behind the offer of pathways that are seductive because they are simple, capable of self-reformulating in response to changes in society and context (Chen, Wang, et al., 2023; Li et al., 2023). While such processes lead to question the value of AI's "creativity" that is the result of the mechanical reworking of pre-existing inputs (Esling & Devis, 2020; Gobet & Sala, 2019), it is important to emphasise the non-deterministic value of neural networks, which generates variations and anomalies that were hitherto considered an exclusive human attribute.

This reading of the state of the art allows us to understand how people who draw with AI take on the role of an "algorithmic curator", like a screenwriter, who writes a film and does not know the actors and the film director that will lead to its realisation. His task is no longer to check every single detail, but to define the rules and parameters within which the algorithm operates. Drawing with AI seems to place the focus in the preliminary phase of representation, in guiding the creative process, selecting and refining the results produced by artificial intelligence, especially when using algorithmic tools at nodes that affect process control. However, we can see the emptying of the content of drawing as a place of knowledge, as a cultural proposal that also has an existential character, offering profound meanings on living and the human condition (Purini, 2022). However, the seductive capacity of images that is enhanced by AI as well as the possibility of learning from the vast amount of data remains of great interest, issues that can be instrumental in the use of this tool for architectural drawing.

The purpose of this study is to investigate the duality of this aspect, which mainly concerns the processes and, firstly, the representative results, which are the aim of the research in affinity with the same aim as the architectural drawing, in the hypothesis that AI can help the drawer to improve certain aspects of the final image produced. In order to achieve these goals, the research focuses on defining a process that, while it will certainly not offer replicability of results due to the non-deterministic nature of neural networks, it is intended to demonstrate how it can offer stochastic results that come close to the set objective, limiting the intrinsic randomness that is inherent in the AI 'obscure' procedures. The proposed digital process aims to 'learn' from the teaching of the masters of architectural drawing, to evoke inhabit through representations but also to search for meanings in these images that can substantiate information content.

In the role of 'algorithmic curators', the aim is to subvert the use of textual semantics by leaving the field of action to drawings, controlling the processes of AI through customised procedures based on nodal and parametric logics, on the assumption that the experimentation tested can extend its field of investigation. Drawing is thus placed at the centre of experimentation, at its genesis and in its outcome, through an innovative process that subverts the quest for simplification and related trivialisation. In the aim of scientificity that animates the research, the purpose behind it lies in reducing the intrinsic randomness that characterises algorithmic processes, governing and directing their causality, so as to generate representations that are in any case original in style and content.

The proposed experimentation is based on the construction of a new digital procedure that connects available digital tools in a workflow, of which not only the final path is described, but also some failures of the experimental activity that thus show the reasons for the choices.

This study therefore proposes as a premise the tools used and the reasons for their selection, and then describes the procedure adopted. An illustrative, replicable and transferable case study is then explained, verifying in its results the stochastic capacity of the process and the impact of the solutions with respect to the interconnected duality of the proposed objectives of application and cultural considerations: on the one hand, it proposes to investigate how artificial intelligence can become an enhancing tool for architectural representation, on the other, it intends to demonstrate how this process can contribute to learning from drawings.

2. *Materials and Methods*

Several complementary tools were used to create the workflow, each with a specific and crucial role within the development pipeline. This architecture integrates innovative solutions and opensource tools, each of which contributes to the construction of a coherent and sophisticated system capable of managing and transforming visual data through an articulated workflow.

The development environment chosen to structure and visualise the algorithm workflow is ComfyUI. The modular interface is based on nodal modelling, allowing each operation to be represented graphically, thus facilitating the understanding and management of the complex interactions between the various components of the workflow. Each node identifies a specific function linked to each other following an operational randomness that allows for easy adaptability and flexibility of processes, consequently enabling optimisation and integration of existing functions. In the conception and articulation of the workflow in question, the Stable Diffusion 1.5 version stands as a fundamental pillar, an advanced image generation model that, by virtue of a previous intensive and in-depth training phase, has reached a degree of maturity and robustness that makes it ideal for further optimisation and customisation through a targeted training process. This model is chosen not only for its intrinsic stability, which guarantees its reliability and consistency in the context of visual generation operations, but also for its excellent compatibility with the various components and tools available online, thus ensuring stable integration and optimal synergy between the various elements of the system.

The module called WD 14 tagger is then used, which is configured as an advanced tagging tool for images. This processing command has an important epistemological function, as it is responsible for assigning semantic tags to the images contained in the assigned dataset. In this way, WD 14 tagger exerts a translating action, transforming visual information, originally perceived in an unstructured form, into textual data that can be interpreted by the algorithm. This semanticisation process is not limited to facilitating the analysis of visual contents, but also extends to their contextualisation, allowing a deeper and more articulate understanding of the meanings intrinsic to the images themselves. The adoption of such a tool is justified, therefore, not only by the need to optimise the algorithm's analytical capabilities, but also by the desire to make visual data, otherwise elusive and complex, more accessible and intelligible, thus contributing to a construction of knowledge that transcends the mere collection of data, to arrive at a true automatic interpretation of visual reality.

With reference to the algorithm training process, it is worth highlighting the use of DreamBooth (Ruiz et al., 2023), a tool that stands out for its ability to customise and implement deep learning models. This element offers the possibility of developing a basic checkpoint, an initial configuration of the algorithm that has already undergone a preliminary training phase on a set of specifically selected images. In more complex terms, DreamBooth is configured as an adaptation mechanism, which allows the system to

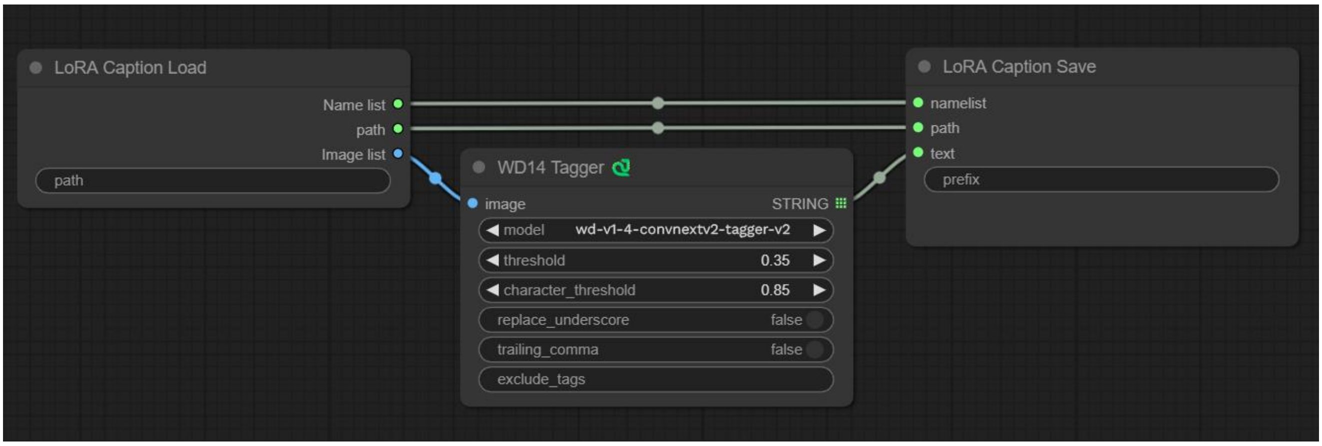

Fig. 2: Graphic visualization of the workflow for using the WD14 tagger internally in ComfyUI

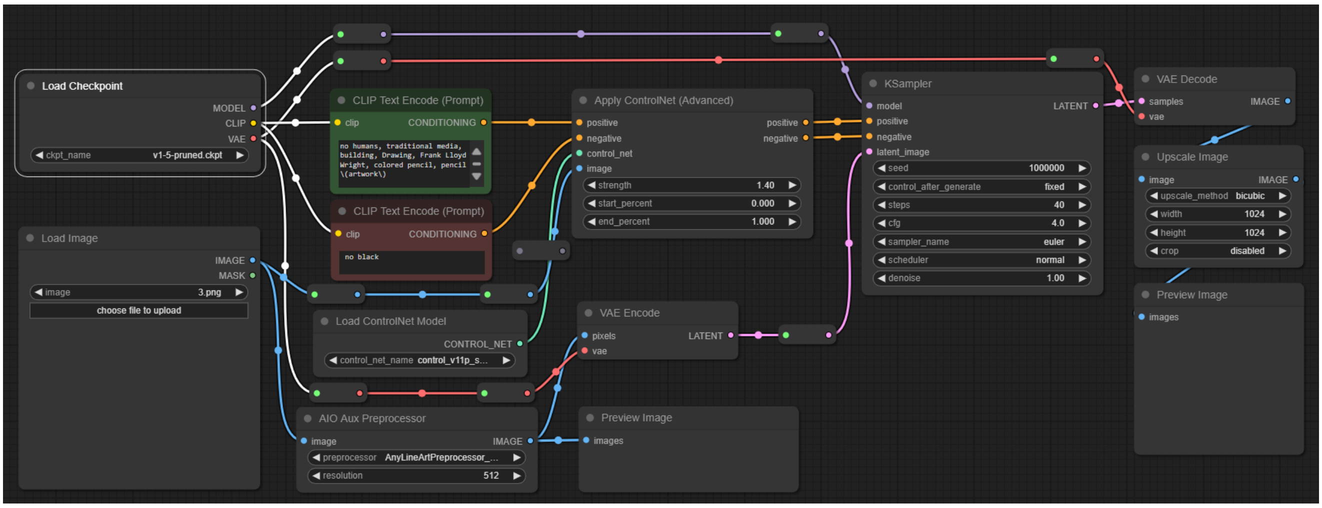

Fig. 3: Workflow structured internally in ComfyUI

be modelled according to specific needs, integrating into the training path not only the visual data, but also the semantic labels processed through the WD14 model, thus enabling an incremental improvement in the performance of the algorithm itself.

The final stage of the workflow includes the nodes "Apply ControlNet (Advanced)" and "AIO Aux Preprocessor", an advanced control framework designed to improve image processing through the application of artificial intelligence algorithms. Its relevance emerges in the tool's ability to apply specific rules and constraints that guide and delimit the interpretation of images by the algorithm. This functionality not only helps to prevent processing errors and unwanted distortions from occurring, but also offers the possibility of exercising granular control over visual properties, so that the final output strictly meets the criteria and expectations established at the design stage.

The workflow is developed through essential steps that include, firstly, the systematic collection of data, followed by the tagging of the dataset, which allows accurate classification of the information. Next, a reference model is created, a fundamental tool for image generation. The result is then guided by a reference image, which guides the creative process. Significantly, the last two steps are realised through visual node management, which facilitates the interaction and efficiency of the system.

The first phase of this complex process, which is indispensable for the architecture of the system, takes the form of a methodological and rational collection of visual data, expressed through a corpus of images that serves as an empirical basis for any subsequent processing. The selection of the initial dataset, which can start from a minimum of ten units and grow progressively according to contingent needs, represents a preliminary step of fundamental importance. In this context, in fact, it is not just a matter of collecting images for their formal or aesthetic consistency, but of making a deliberate choice that takes into account their intrinsic quality and their suitability for the subsequent phases of computational processing. Images are not, therefore, mere reflections of an empirical reality, but, in their semiotic essence, are configured as true vehicles of meaning, raw in their original form, but destined to be transmuted through a process that makes them interpretable in computational terms. To this end, the selected images must be subjected to a pre-processing process that unifies their dimensions, preferably to 512x512 pixels, thus optimising the dataset for the subsequent training phase, in which the model will be able to take maximum advantage of a coherent and uniform database in terms of technical specifications. The choice of this specific resolution is dictated by pragmatic reflection, this size being suitable to be handled by all components of the system without incurring problems of incompatibility or future inefficiencies.

Following the preliminary phase of image acquisition, tools are used that are capable of attributing explicit and articulated meaning to the collected visual data, enabling a critical and systematic reading of their content. To this end, we opted for the implementation of the WD14 tagger executed within the ComfyUI interface, which stands out for its superiority over other available open-source taggers, thanks to its extended compatibility with a plurality of operating systems and training on a specific and refined dataset, particularly suitable for decoding images with an architectural character. The core of this process lies in the tagger itself, for which the model "SmilingWolf/wd-v1-4-convnextv2-tagger-v2" was selected, chosen for its ability to detect complex details and highly sophisticated visual patterns, making it ideal for the detection and classification of shapes, materials, structures and other relevant components of images related to buildings, infrastructure and projects of architectural character. In addition, the operational architecture makes use of LoRA technology (Hu et al., 2021), applied in both input and output through the use of Lora Caption Load and Lora Caption Save nodes. The first node, "Load," plays a dual role: on the one hand, it sends the images to the tagger for processing; on the other hand, it extracts and records the names of the files in the selected directory. Subsequently, the list of file names and their generated captions are sent to the "Save" node, which provides for the creation of text files, each named after the corresponding image file and containing the textual description derived from the tagger's analysis. It is relevant to note that no other parameters are changed during the process, the outcome of which results in the generation of .txt files that enclose a detailed textual description of the analyzed images, providing a semantic representation of their visual content.

Once the preliminary semantic classification phase is completed, a reference model, called a checkpoint, is placed, which assumes the role of operational foundation and starting point for subsequent algorithmic processing. With this in mind, it was decided to avoid the ex-novo development of such an element, a choice dictated by the inherent complexity of the training process, which requires not only a considerable amount of data, but also an enormous computational capacity. Therefore, a pre-existing basic model was adopted, to be implemented with the fine-tuning process identified in Stable Diffusion version 1.5, which proved adequate for the purposes of the project. Specifically, in order to make improvements to the model, it was chosen to employ the locally executed DreamBooth algorithm, which, due to its flexibility and accuracy characteristics, is optimally suited to target model training to the provided dataset, improving the system's generalization capability with respect to new inputs. This customization process is further enhanced by the use of the previously made taggers, which allow the training process to be more precisely directed toward the specifics of the provided images.

The final phase, represented by the actual implementation of the algorithm, takes place through the use of the ComfyUI interface, a visual environment that allows the algorithm's operational flow to be built by means of a modular structure articulated on nodes, each of which embodies a specific operation or transformation applied to the data. This nodal structure, whose interconnection is governed by strict deterministic logic, faithfully reflects the intrinsic operation of the underlying model. Specifically, the first significant operation within the flow is the loading of the base model, which has been previously implemented through fine-tuning techniques. This operation is performed through the node called "Load Checkpoint" which allows loading the optimized weights and architectures of the model, as defined in the preliminary stages of the process.

Next, the "CLIP Text Encode" node allows both positive and negative textual prompts to be introduced into the workflow, which serve as a guide for image generation. These textual inputs are processed in parallel and conveyed to the "Apply ControlNet (Advanced)" module, which performs a crucial function: through the ControlNet model, in fact, a careful control over the final result is exercised starting from certain input data figuring the initial image, preserving its geometric structure and shape arrangement, but at the same time allowing a radical transformation of the overall aesthetics, with a real stylistic overwriting. A key parameter at this stage is the "strength", which determines the degree of influence exerted by the module on the image, accompanied by the two factors "start percentage" and "end percentage" that help define the number of steps for applying ControlNet.

For proper operation, ControlNet requires two types of input: on the one hand, the image to be modified, which is input through the "Load Image" node, and on the other hand, the selected ControlNet model, which governs the transformation mode of the image itself. Contextually, the input image is further processed through a module called “AIO Aux Preprocessor”, whose task is to extract key elements from it, depending on the chosen model. However, in order for the image to be used in subsequent steps, it must first be converted to a latent space, an operation that is done through the “VAE Encoder” node. This conversion is essential to allow the model to process the image in a computationally tractable format.

Once the image has been converted to latent space, it is combined with the model and ControlNet data within the “KSampler” node. This module has the function of sampling images following a set of parameters that influence the final result. The main parameters include: the “steps”, which indicate the number of iterations used to progressively improve the quality of the generated image; the “cfg” (Classifier-Free Guidance), which adjusts the level of adherence of the image to textual prompts; and finally the “denoise” parameter, which manages the amount of noise removed during the sampling process, thus determining the clarity and definition of the final image. After sampling, the latent image is decoded in the visual space via the “VAE Decoder” module, which has the task of reconstructing the visible image from the latent representation, translating the numerical output into an interpretable and viewable format. Finally, optionally, the image can be further processed via the “Upscale Image” node, which allows it to be enlarged to the specified size, improving its resolution without compromising visual quality.

3. *Case Study*

The digital procedure has been tested with several datasets, of which the significant case study based on the drawings of the great master Frank Lloyd Wright is shown here. The richness and clarity of representation, in addition to being highly recognizable stylistically, expresses contents in the relationships between architecture and landscape, which are inherent in the contents and meanings of his organicistic work (Pfeiffer & Goessel, 2015). Wright's drawings are distinguished by a fluid, almost organic stroke, which, despite its apparent simplicity, reveals a complex interrelationship between the geometry of architectural forms and their surroundings. The lines, marked and incisive, precisely delineate volumes that are never merely functional, but represent a constant dialogue between architecture and landscape (Hoffmann, 1995). The use of color, while remaining subtle and often discreet, suggests a deep understanding of light as a compositional element and materiality as an essential component of spatial experience. His drawing style is never merely illustrative but becomes a means of communicating a holistic architectural vision, where the detail of the fragment never loses sight of the unity and coherence of meaning of the proposed architecture that thrives on its relationships with its surroundings (Zevi, 1947). It is precisely this visual clarity, combined with the poetic dimension that emerges from the connection with the context, that gives his sketches a status as autonomous artistic works, as well as design tools. In order to validate the workflow described in the

Control_v11p_sd15_lineart.pth	**Control_v11p_sd15_canny.pth**	**Control_v11p_sd15_depth.pth**	**T2i-adapter_diffusers_xl_lineart.safetensor**

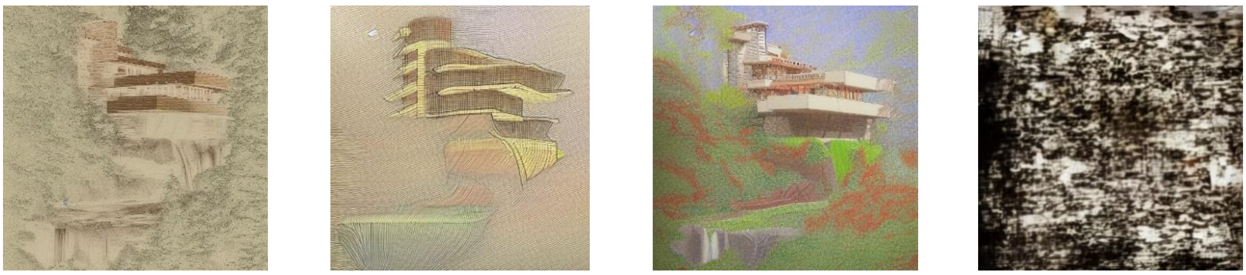

Fig. 4: Analysis of output results by keeping AIO Aux Preprocessor constant on “AnyLineArtPreprocessor” and changing ControlNet templates.

methodology, the research first aims to apply Wright's drawing style to actual photos of his architecture, thus being able to have direct feedback on the actual effectiveness of the algorithm, and then to be a ble to apply the same process to other case studies. In this context, the result posed as a goal is not limited to a simple imitation of Frank Lloyd Wright's style, but seeks to explore new formal variations, posing as a critical reflection on the aesthetic and geometric principles underlying his creations. The algorithm created is not simply faced with the task of replicating visual forms, but rather with the task of understanding and reproducing a conceptual structure that is at once aesthetic, functional and philosophical, in order not to limit itself merely to the emulation of Wright's works, but to reinterpret them through algorithmic innovation, expanding the boundaries of expressive possibilities without

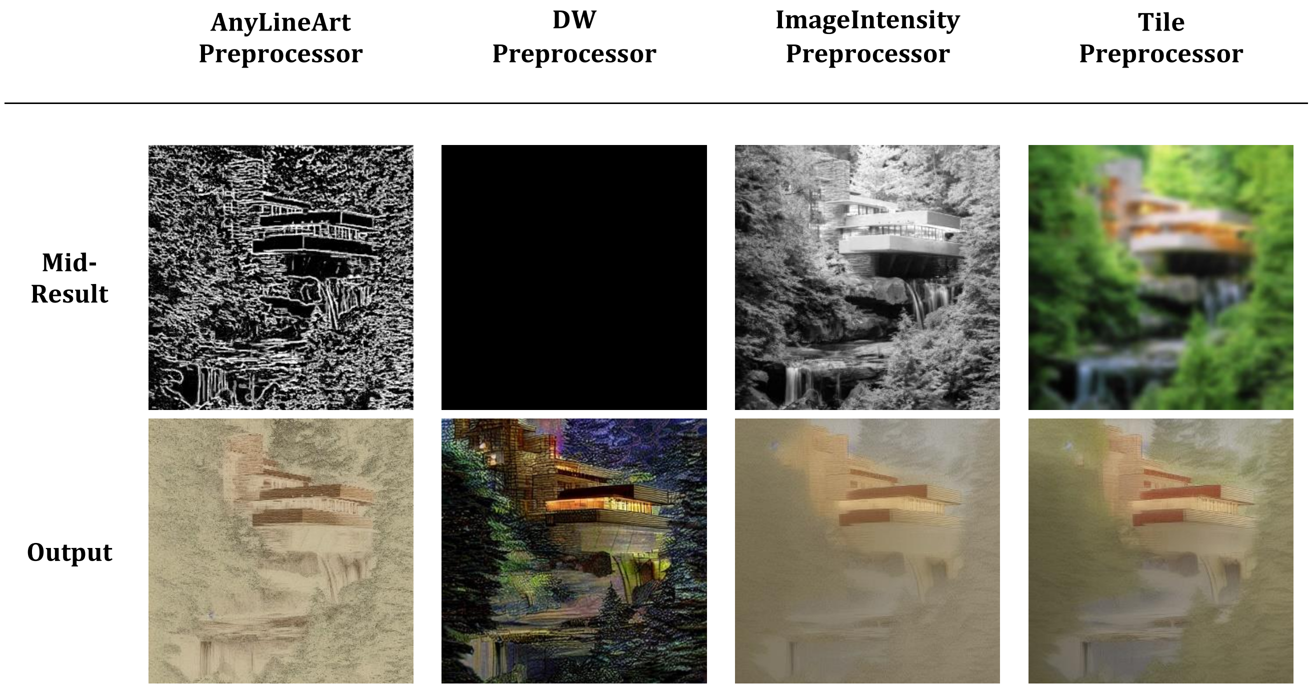

Fig. 5: Analysis of output results by keeping ControlNet constant on "control_v11p_sd15_lineart.pth" and modifying AIO Aux Preprocessor templates.

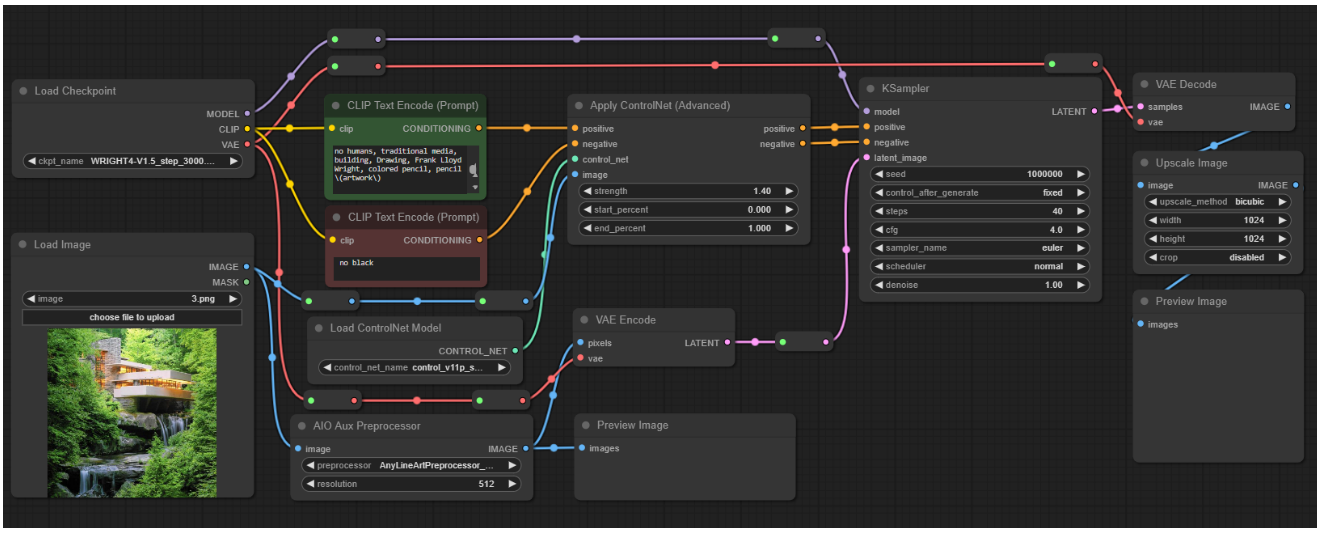

Fig. 6: Application of Workflow to the case study.

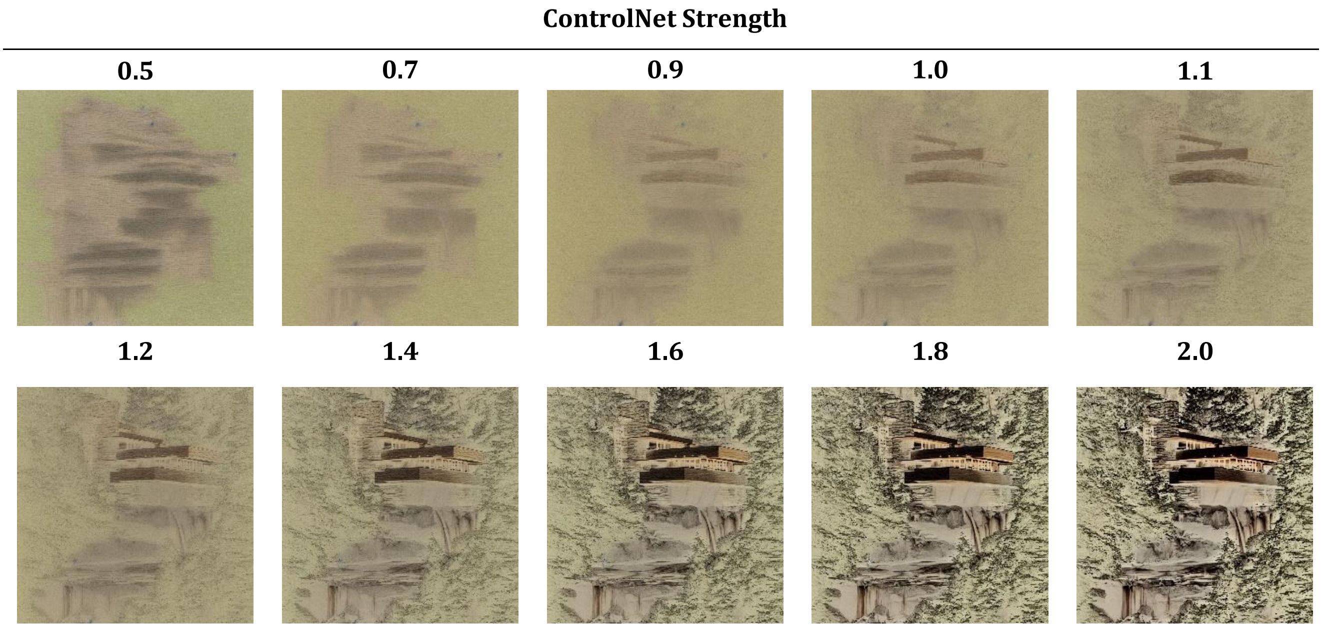

Fig. 7: Variation of Output in correlation with the value of ControlNet Strength

ever losing sight of the internal coherence of the principles that guided the American architect.

Following up on what was explained in the section on methodology, the first step was to collect a set of Wright's drawings, taken from “The Frank Lloyd Wright Digital Archive” shared by Columbia University, from where 40 drawings were selected for training, chosen with the criterion that they illustrate several of his works while maintaining a consistent and homogeneous graphic style. The database thus formed constitutes the starting point on which to set up the semantization process using “tagger W14”, which returned a common description via keywords of the chosen images, for the purpose of fine-tuning the “v1-5-pruned.ckpt” model via Dreambooth, which was installed locally. The proper performance of these two operations resulted in a Checkpoint, in .ckpt format, to serve as the basic model of the algorithm in ComfyUI. It was chosen to include in the “CLIP Text Encode” the most recurring semantic cues in the training such as “no humans, traditional media, building, Drawing, Frank Lloyd Wright, colored pencil, pencil \(artwork\)” to direct the output more towards the result sought. The results obtained through the application of these first nodes showed initial positive outcomes of processing the input image, which, however, needs further and more in-depth iterations. Consequently, the use of different types of ControlNet was experimented with to gain further control over the final output of the produced images, while experimenting with correlation with the AIO Aux Preprocessor node. Taken together, these algorithms allow for adjustment, which originates in the analysis of the input image in a variety of areas such as contour lines, backgrounds, color scales, and depth, thus allowing the process to be projected toward a range of potential stylistic languages that are profoundly dissimilar from one another. In our specific case study, the results closest to the goal were obtained by adopting the models “control_v11p_sd15_lineart.pth” as ControlNet and “AnyLineArtPreprocessor” as AIO Aux Preprocessor. A direct qualitative comparison of the multiple results observed showed that the chosen pair of models allows a graphical rendering close to the desired one, while other variations, while almost always remaining faithful to the style of hand-drawing conveyed by the fine-tuning of the basic checkpoint, offer outcomes that often move toward far too different graphical styles.

Once the main templates to be used and the source image have been established, the workflow created in ComfyUI appears as in Fig. 6. The components described above are the ones that have been shown to have the strongest influence on the result, as they establish how the starting image is to be interpreted graphically. Conducting an analysis on the variation of the adjustment parameters of the nodes which were used, it was found that these do indeed allow the modification of some graphical aspects related to processing, but also that the same affect less than the training process and the choice of ControlNet and AIO Aux Preprocessor models. Specifically, the analysis that produced most interesting considerations is the one related to the ControlNet application parameters with the "Apply ControlNet (Advanced)" node, as per Fig. 7.

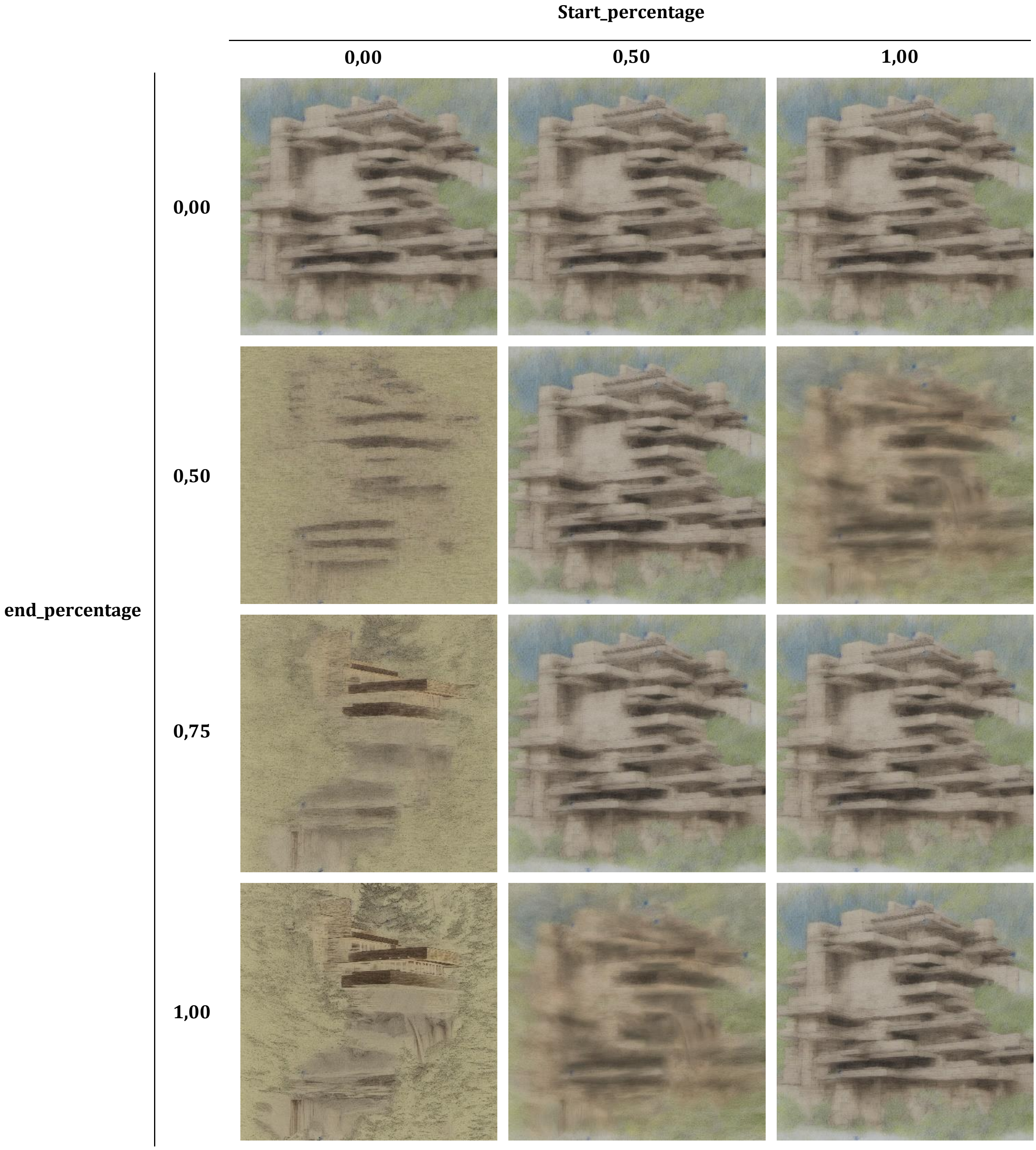

Fig. 8: Displaying outputs by keeping the Strength: 1.4 value constant and varying the end_percentage and start_percentage ones

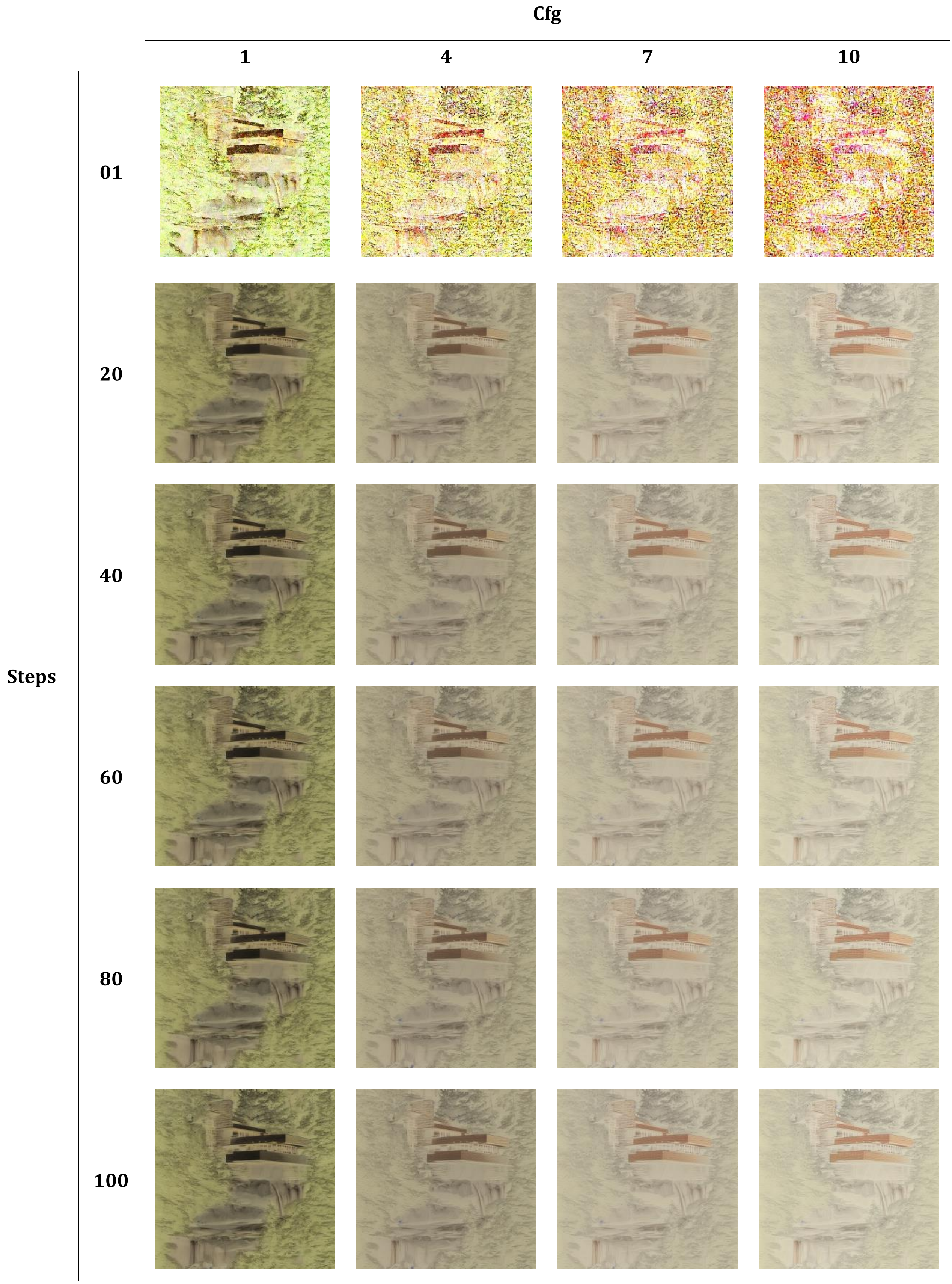

Fig. 9: Displaying outputs by keeping the value Seed: 0 constant and varying Cfg and Steps.

First, in order to have full awareness of the exact effect of each parameter, dissociated analyses were conducted in which to vary one value at a time. Keeping the gap between "start_percentage" and "end_percentage" fixed, the effect of the strength parameter was first investigated, which was shown to allow a variation in the intensity of application of the model loaded as the initial Checkpoint, producing gradually more defined images with higher contrast.

By performing the reverse operation, on the other hand, it became clear that the node is also critical for reading the shapes present in the original image, since cases in which the gap between the two parameters for adjusting the application percentage is less than 0.75, corresponding to 75 percent of the total processing steps, return a completely inaccurate final representation of the geometric shapes present. Similar considerations can be made for all cases in which the values of start_percentage exceed those of end_percentage, as the node fails to process the images correctly by working with percentages that start from high values and arrive at lower values, namely with negative percentages.

Other parameters that have been shown to affect the graphical rendering of the final image are those related to the "KSampler node", which is necessary in the algorithm to correlate the ControlNet to the preprocessed image with the "AIO Aux Preprocessor", while presenting a minimal impact on the graphical rendering. Conducting dissociated analyses again aimed at studying the effect of individual parameters, it was

Checkpoint	Clip Text Encode	ControlNet Model	AIO- Aux preprocessor	Apply ControlNet	KSampler
Wright 1.5	**Positive**: no humans, traditional media, building, Drawing, Frank Lloyd Wright, colored pencil, pencil \(artwork\)	**control_v11p_sd15_lineart.pth**	**AnyLineArtPreprocessor**	**Strength**: 1.4 **Start_percentage**:0.00 **End_percentage**: 1.00	**Seed**: 0 **Steps**: 60 **Cfg**: 7

Fig. 10: Optimal values for the use of workflow.

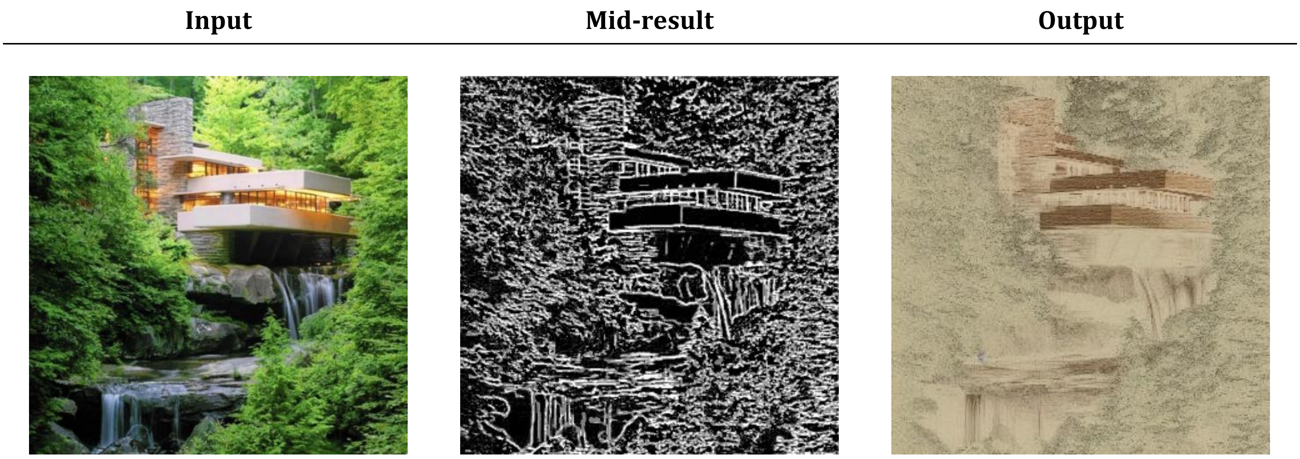

Fig. 11: Graphical summary of the process, from the initial input image to the mid-result and finally the Output.

found that the variation of the value related to "seed" directly affects color saturation and contrast. The other parameters associated with it, on the other hand, presented less weight: with reference to the values of "steps" and "cfg," in fact, it can be seen that these do not affect geometric processing, stylistic rendering or definition at all, affecting on the contrary only slight aesthetic adjustments such as brightness and contrast. This is probably related to the sequence of nodes used in our algorithm, in which the KSampler intervenes only in the final stage of image processing as a reprocessor of the data already produced by the checkpoint obtained by fine-tuning, the positive and negative prompts, the AIO Aux Preprocessor and the ControlNet.

Following these iterations, it can be asserted that the best values for using and controlling this algorithm and obtaining output images similar to Frank Lloyd Wright's drawing style, are those shown in Fig. 10 obtaining the results present in Fig. 11. After completing the preliminary testing and validation phase, the developed workflow was applied to a series of drawings produced by various architects in order to assess the effectiveness of the style transfer process exposed in Fig. 12 and Fig.13.

4. Conclusions

The proposed experimentation demonstrates how AI can help with drawing.

The results, although stochastic, are close to the style of drawings that are taken as reference. The experimentation conducted demonstrated the achievability of the intended goals, namely, to exert significant "control" over artificial intelligence and the results it generates. In particular, the algorithmic process developed within ComfyUI proved capable of effectively and consistently translating the distinctive style of Frank Lloyd Wright, producing drawings that retain the essential and unmistakable characteristics of his architectural poetics. An analysis of the application of the procedure on drawings and images by other authors is shown to be akin to the mode of representation with which AI has been trained. In this context, drawing, traditionally conceived as a controlled and deliberate process, is transformed into an act of co-creation, where the architect, in symbiosis with the algorithm, becomes the spokesperson for an unprecedented and profound creative synergy.

The complexity of the algorithmic procedure, which becomes of interest to those involved in research, is offered as a replicable solution to fully exploit the potential of AI for architectural drawing. Experimentation can be useful to improve the quality of drawings or to transform their meaning. If the digital procedure developed here, after AI training, is tested on a single author's drawings with the aim of verifying the quality of the results, it can be used to mix styles and discover the author's own graphic signature, understanding the meanings derived from the medium.

It can be emphasized that the whole-process approach can be understood as a path of progressive abstraction, in which raw visual data are first organized, then semantized, and finally transformed into input for an artificial intelligence system, culminating in the creation of an operational model capable of processing such data independently and sophisticatedly. It is crucial to emphasize that such control, achieved through experimental experience, should not be interpreted solely as mere technical dominance. On the contrary, it must be conceived as a dialectical synergy, in which the human mind and the machine contribute their own distinctive peculiarities to a shared creative process.

This shows how the role of algorithmic curator, which was already the basis of generative design processes, persists even with AI, which imposes cultural reflections integrated with increasingly advanced skills in digital representation. Just as continuous practice is necessary in manual drawing, so too in drawing with AI it is necessary to put forth the will to innovate and experiment, attending to processes and paying attention to the results produced, directing the tool, which by itself is never that intelligent, to achieve the goals to which representation continues to strive continuously throughout history, even beyond technology. However, AI shows itself as a *techné*, as a tool and an art, as a medium that affects the message. Through a profound renewal of representational research itself, AI can become a tool whose results are controlled and therefore can aid drawing.

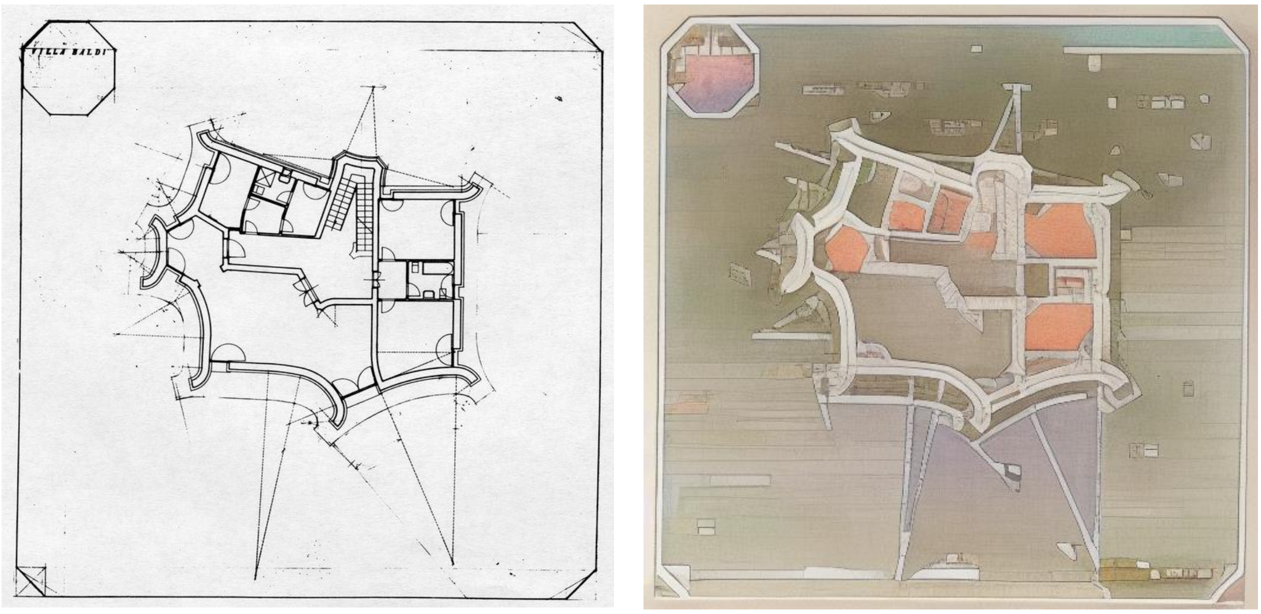

Fig. 12: Displaying outputs by using drawings of Paolo Portoghesi as input in the workfllow.

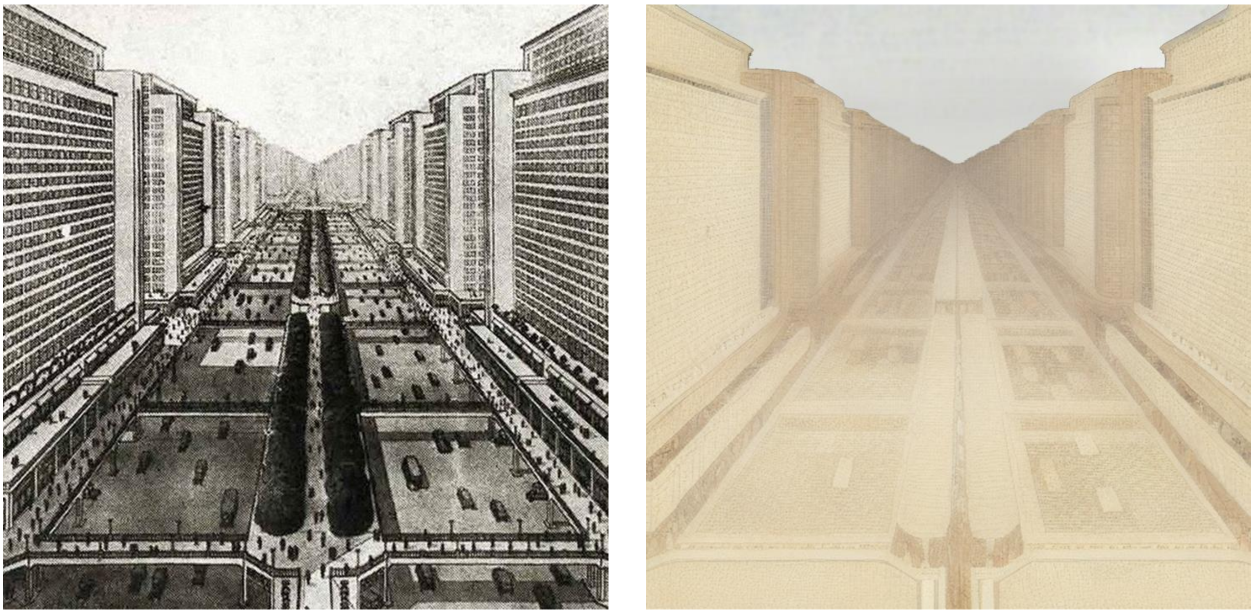

Fig. 13: Displaying outputs by using drawings as Le Corbusier input in the workfllow.

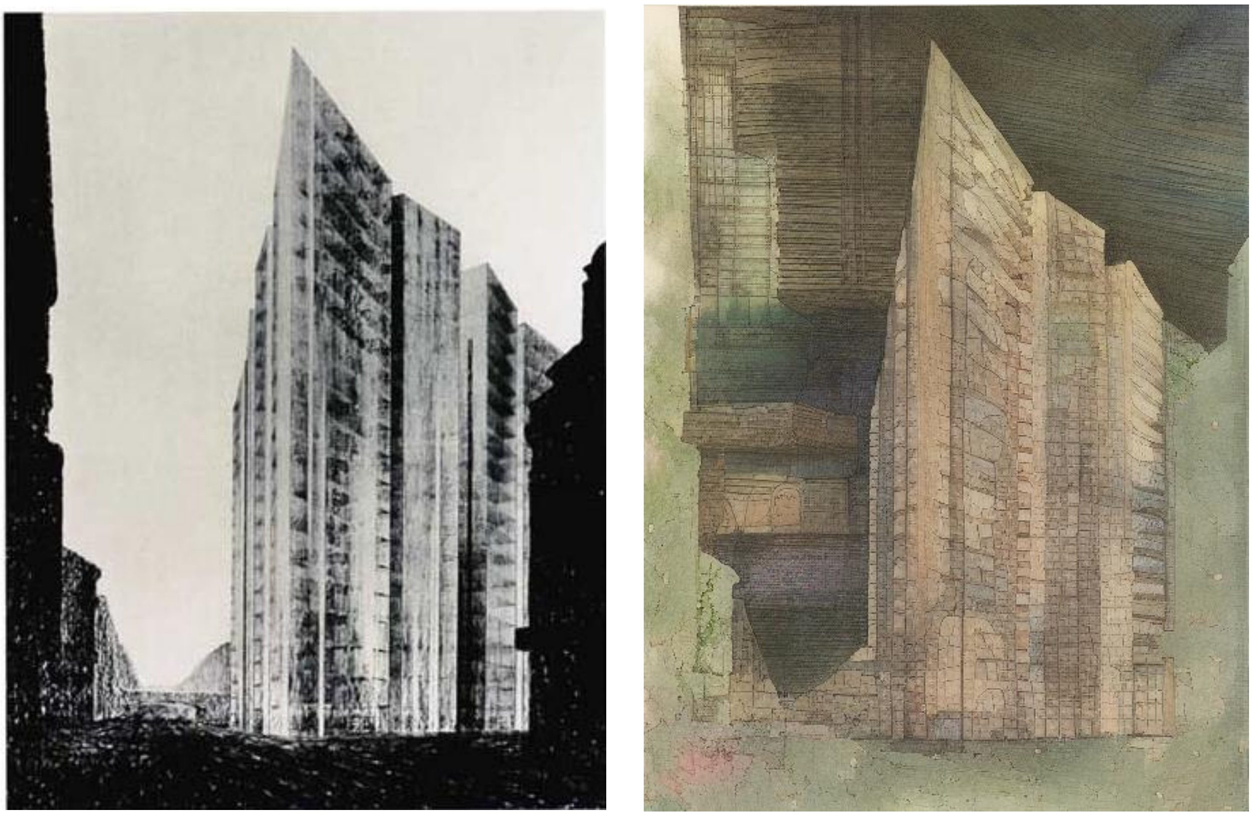

Fig. 14: Displaying outputs by using drawings as Mies van der Rohe input in the workfllow.

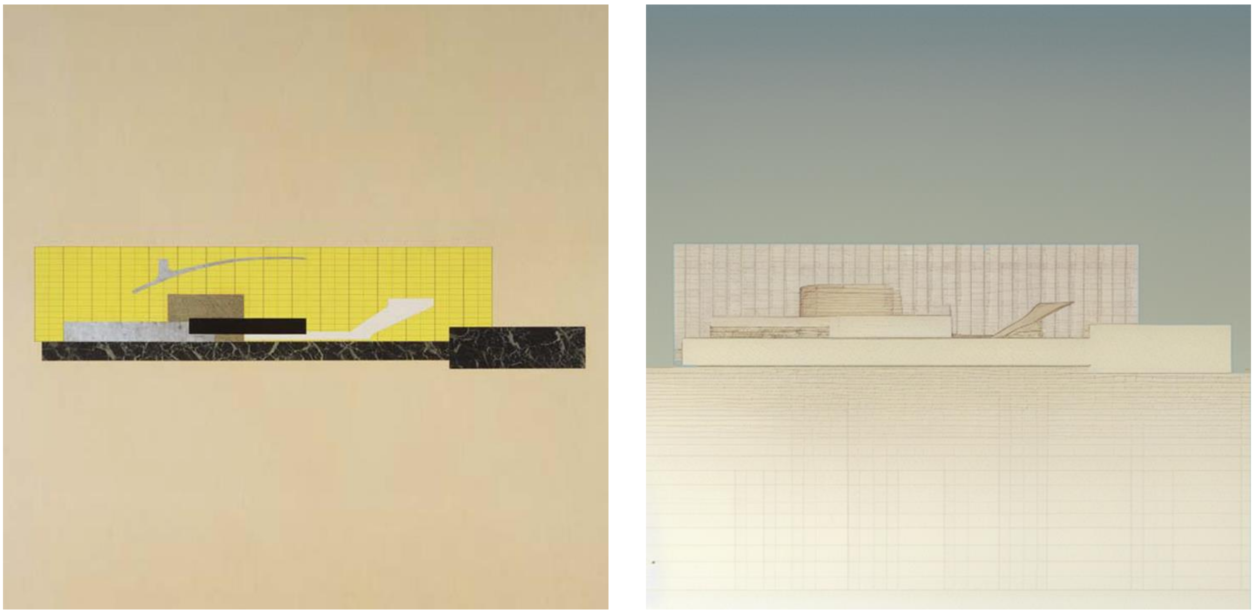

Fig. 15: Displaying outputs by using drawings as Mies van der Rohe input in the workfllow.

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