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Automated Chipboard to Edge Band Matching

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***Abstract*—In the furniture industry, chipboard is a widely used material due to its cost-effectiveness and versatility. However, matching chipboard surfaces with aesthetically and functionally compatible edge bands remains a critical and challenging task, often performed manually based on subjective judgment. This paper presents a novel chipboard edge band matching system that leverages one-shot learning with Siamese networks to automate and optimize this process. The system employs CNN-based Siamese Networks to analyze and quantify the similarity between chipboards and edge bands based on multiple criteria, including color, texture, pattern, and shape. A comprehensive similarity model and a similarity value table are generated, enabling manufacturers to identify the most compatible edge bands for any given chipboard. In addition, this study contributes to the field by introducing an open-source dataset publicly available containing chipboard and edge band samples. This dataset provides a valuable resource for researchers exploring industrial material matching and computer vision applications. The proposed system addresses the limitations of existing methods, offering an efficient, scalable, and objective solution for edge band selection. By bridging the gap between manual processes and advanced automation, this work aims to improve production efficiency, consistency, and aesthetic quality in the furniture manufacturing industry.**

***Index Terms*—one-shot learning, Siamese networks, chipboard to edge band matching**

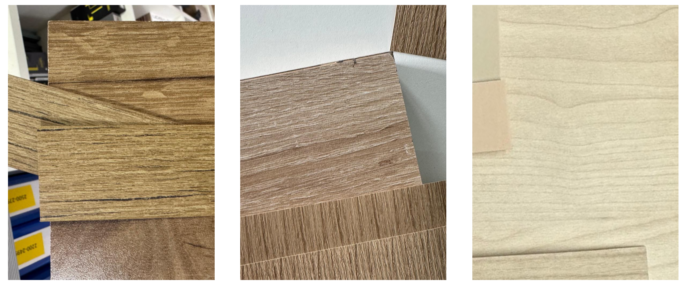

Fig. 1. A set of unmatched chipboards and edge bands

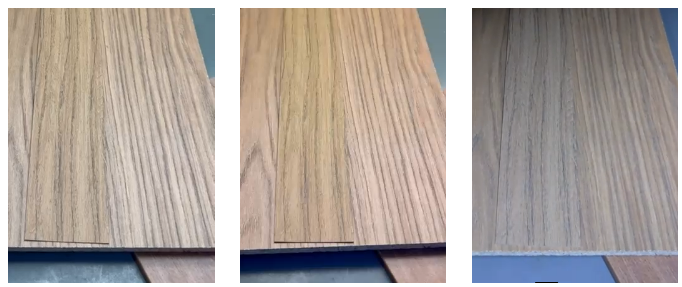

Fig. 2. The same chipboard and edge band pair under different lighting conditions

I. Introduction

In the furniture manufacturing industry, chipboards are widely used as a cost-effective core material. These boards can be painted and coated in thousands of colors, patterns, and textures to suit aesthetic preferences and evolving design trends. However, after covering their broad surfaces, the edges remain exposed and require matching edge bands for both functional and aesthetic purposes. Edge bands, typically plastic strips, are crucial components in modernizing furniture by concealing cut edges and providing a cohesive finish.

Determining the most suitable edge band for a chipboard has traditionally relied on subjective visual assessment, which poses challenges in achieving optimal matches (See Fig. 1). Factors such as variations in color, texture, pattern, and material properties between chipboards and edge bands make manual matching labor-intensive and prone to inconsistencies (See Fig. 2). Moreover, differences in production processes, scaling, and material composition further complicate the task of achieving alignment between the two.

The manual selection of edge bands for chipboards in the furniture industry is inefficient, subjective, and prone to errors. Most of the time, either a new edge band production cannot be matched with the target chipboard, thus leads to waste of time, labor and resources. Or else, a suitable edge band in the inventory cannot be pinpointed, leads to repeated production of the same or very similar edge band with an additional cost and effort.

Key challenges include:

- **Visual Inconsistency:** Human perception varies significantly, making it difficult to achieve consistent matches for complex criteria like color, texture, and pattern.
- **Material and Production Variability:** Differences in materials, production processes, and scaling between chipboards and edge bands often result in mismatches that compromise aesthetic quality.
- **Time and Labor Intensity:** Relying on manual inspection is time-consuming and demands skilled labor, which may not always be available.
- **Lack of Automated Solutions:** Existing technologies focus on identifying object types or physical properties but lack the capability to perform precise compatibility matching.

To address these issues, a robust, automated system is needed that can analyze multiple attributes of chipboards and edge bands to produce reliable and consistent matches. The chipboard to edge band matching system proposed in this paper aims to fill this gap by leveraging machine learning and similarity modeling to streamline the process.

It is claimed that the proposed system will outperform traditional manual methods in matching chipboards to edge bands in terms of accuracy, efficiency, and consistency. Specifically, the hypothesis is: *by employing convolutional neural networks to analyze visual and material properties, the chipboard to edge band matching system can reliably identify the most compatible edge bands for chipboards, achieving higher precision and consistency compared to expert opinion based methods.*

This paper introduces a novel chipboard to edge band matching system designed to automate and optimize the precise pairing of chipboards with their most compatible edge bands. The proposed system operates by scanning chipboards and edge bands from various manufacturers, feeding the data into a Siamese neural network to measure Euclidean distances and establish compatibility relationships. This process culminates in the creation of a *Similarity Model* and a comprehensive *Similarity Value Table*, which quantify the compatibility between chipboards and edge bands. When a new chipboard is introduced, the system evaluates it using the similarity model and identifies the most suitable edge bands, presenting the results in a user-friendly digital format.

The key contributions of this work include:

- **Automated Matching Process:** Development of a system that eliminates subjective, manual processes by leveraging deep learning and Siamese neural network methodologies.
- **Similarity Model Creation:** This study applies Siamese neural networks, specifically based on ResNet-50, to analyze and quantify the similarity between chipboards and edge bands. The novelty of the contribution lies not in developing a new Siamese network architecture but in its application to the industrial problem of chipboard-edge band matching. The model effectively captures multiple aesthetic and physical criteria—including color, texture, pattern, and shape—providing a robust and automated solution for similarity measurement in this domain. Additionally, by leveraging the similarity model, the system can predict suitable edge bands even for previously unseen chipboard patterns. This is a significant practical contribution, as it enables the model to infer matches for unfamiliar designs based on learned similarities from known samples. In essence, the system enhances decision-making by allowing meaningful predictions about unseen cases using prior knowledge.
- **Comprehensive Similarity Metrics:** Generation of a similarity value table that serves as a reference database for identifying the most compatible edge bands for any given chipboard.
- **Dataset:** Publication of a large-scale, open-source dataset comprising chipboard and edge band samples. This dataset is a valuable resource for further research on industrial material matching and computer vision-based solutions in the furniture industry. All images are acquired by scanning with a standard scanner. This approach ensures that additional data can be seamlessly incorporated into the database using off-the-shelf scanning devices. The current data set is obtained with a standard commercial scanner via the respective product's standard software in 300 dpi resolution.
- **Practical Use in Furniture Manufacturing:** A system scalable to industry requirements, enabling manufacturers to achieve consistent and aesthetically appealing results while saving time and reducing errors.
- **Inventory Management:** A similar edge-band finder system with respect to given chipboards make inventory management mush more efficient as it is common to produce an existing or very similar edge band multiple times when it cannot be found at first try. The results shown in § V validates this claim.
- **Product Line Robustness:** In an industrial production facility, it is common that the laborers, configuration and calibration of devices are apt to change. Therefore, the products might lapse into distorted decorations in time. Matching the initially approved edge band with later products guarantee better assessment and helpful for quality assurance of the facility.

By providing both an innovative solution and an open-access dataset, this work not only addresses a specific industrial problem but also fosters further research and innovation in the field of automated material compatibility determining systems. This innovative system eliminates the need for subjective judgment in edge band selection, providing an efficient, and scalable solution for the furniture industry. By addressing long-standing technical and practical challenges, the chipboard to edge band matching system paves the way for enhanced design coherence and streamlined production processes.

II. Literature Review

Antoniuk et al. applied Siamese networks to recognize drill wear in manufacturing processes. Their approach involved comparing images of new and worn drills to assess wear levels, enhancing predictive maintenance strategies [1].

Musmeci et al. utilized hybrid Siamese neural networks for object reidentification in aerial photographs. This method improved the accuracy of tracking objects across multiple images, benefiting surveillance and environmental monitoring [2].

Hindy et al. leveraged Siamese networks to develop a one-shot intrusion detection model. This approach enabled the system to identify new types of threats by comparing them to known attack patterns, improving cyber-security measures [3].

Zhou et al. proposed a Siamese neural network based few-shot learning method for anomaly detection in industrial cyber-physical systems. Their model effectively identified anomalies with limited data, enhancing system reliability [4].

Kristoffersen et al. introduced SiamTST, a representation learning framework integrating a Siamese network for multivariate time series forecasting in telecommunication networks. This model improved forecasting accuracy, aiding in network management [5].

These studies demonstrate the versatility of Siamese networks across various industrial applications, including manufacturing, surveillance, medical imaging, cyber-security, and telecommunications.

Siamese networks have been applied to fabric classification and matching tasks. For instance, a study utilized Convolutional Neural Networks (CNN) and Siamese networks to classify and match fabric patterns, aiding in efficient textile pattern recognition [6].

In the realm of product authentication, Siamese networks have been employed to detect counterfeit items. A study proposed a Siamese Neural Network that uses two sub-networks to validate product authenticity, demonstrating effectiveness in distinguishing genuine products from counterfeit ones [7].

These examples illustrate the versatility of Siamese networks in addressing complex industrial challenges, particularly in areas requiring precise matching and verification.

Siamese networks have been effectively utilized in defect detection across various industries. For instance, a study proposed a change-aware Siamese network that addresses defect segmentation through a change detection framework. This model compares images of defect-free and defective surfaces to identify anomalies, achieving high-quality pixel-wise defect detection [8].

In another application, a real-time, unsupervised learning Siamese defect detection network was developed based on knowledge distillation. This approach enables efficient and accurate detection of surface defects in manufacturing processes without the need for labeled defect data [9].

These examples demonstrate the versatility of Siamese networks in identifying and segmenting defects, contributing to improved quality control in industrial settings.

Similarly, recent research in furniture manufacturing has explored deep learning techniques for automating visual inspections. For instance, a study by Chen et al. developed a deep learning-based system for detecting defects in edge-glued wooden panels, aiming to improve quality control in furniture production [10].

Additionally, computer vision technology has been integrated into furniture manufacturing workshops to achieve effective and high-quality production modes, as discussed by Li et al. [11].

However, limited studies have focused on the specific problem of chipboard to edge band matching.

This study applies a ResNet50-based Siamese Network with techniques which suggested by Schroff et al. [12] to enhance the learning of feature embeddings and achieve high-accuracy chipboard-edge band matching.

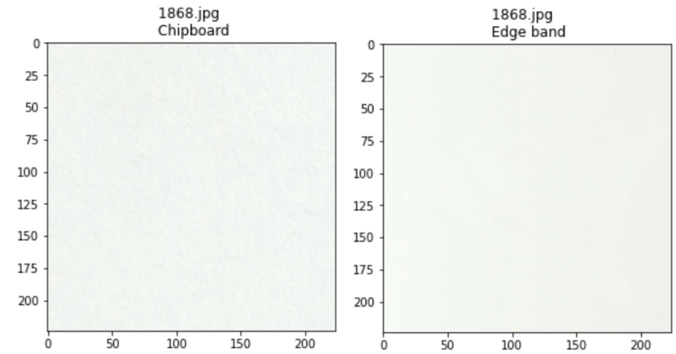

Fig. 3. A simple chipboard and edge band pair matching is prioritized.

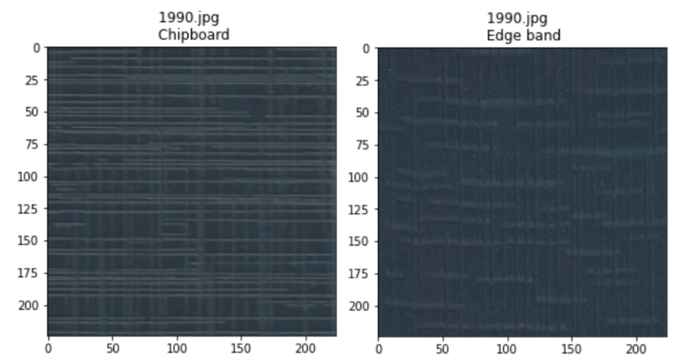

Fig. 4. A chipboard and edge band pair. Even though a texture is present, only the color matching is important.

III. Dataset

A comprehensive dataset of chipboard and edge band images was collected from a global edge band manufacturer.

The dataset includes:

- **Chipboard images:** 2433 high-resolution images of various chipboard surfaces, including different colors, textures, and patterns.
- **Edge band images:** 3435 high-resolution images of edge band materials categorized by their corresponding chipboards.

Domain experts labeled each edge band with its matching chipboard with the same image names to create a ground-truth dataset in separate chipboard and edge bands folders. The dataset consists of two distinct types of chipboards and edge bands, categorized based on their decoration. The first type is marked with names starting with “1” (e.g. 1234), which feature no patterns or very simple patterns where only color matching is the primary criterion (See Fig. 3). There are 650 chipboards and 969 edge bands of the first type in total. As illustrated in Fig. 4, while some texture variations may be visible in these images, they do not significantly impact the matching process.

The second type has names that do not start with “1” (e.g. 4321), which exhibit complex patterns where the complete decoration (both color and pattern) play a crucial role in the matching process (See Fig. 5). In these cases, the model must capture not only color similarity but also intricate design

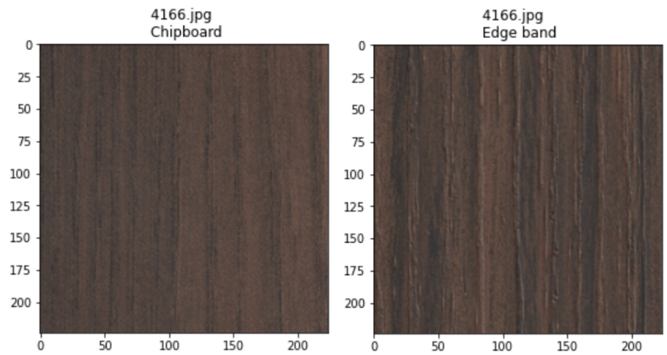

Fig. 5. A complex chipboard and edge band pair where both the color and the pattern are important.

structures to ensure accurate recommendations. There are 1783 chipboards and 2466 edge bands of the second type in total.

To prevent potential confusion between these two categories—particularly due to texture artifacts in simple designs that might resemble complex patterns—the dataset is processed separately for each category. This ensures that the model effectively learns the appropriate matching criteria for both simple color-based bands and complex patterned designs.

IV. Methodology

The methodology consists of four steps: data cleaning, image preprocessing, determining the model architecture and configuration of the model.

A. Data Cleaning

In this phase, incorrect chipboard-edge band matches were identified and removed. This process was conducted manually by evaluating all matches in the dataset to ensure accuracy. Additionally, chipboards that did not have a corresponding match in the edge band dataset were also excluded. These steps were critical for maintaining the integrity of the dataset and ensuring high-quality training data.

B. Image Preprocessing

Image preprocessing consists of pixel-wise intensity normalization and resizing.

- **Normalization:** Images were normalized to have pixel intensity values between 0 and 1.
- **Resizing:** All images were resized to 224 × 224 pixels to ensure uniformity and compatibility with the architecture of the model.

C. Model Architecture

The model utilized in this study is a Siamese Network with ResNet50 and Triplet Loss. To enhance the accuracy and robustness of the chipboard-edge band matching system, a Siamese Network was implemented using ResNet50 as the backbone for feature extraction, coupled with a triplet loss function and semi-hard batch mining strategy. The components of the model is described below.

- **Base Model:** A ResNet50 model pretrained on ImageNet was employed for feature extraction. The weights of all layers up to the output of the fifth convolutional block's first residual unit layer (conv5-block1-out) were frozen to preserve the pretrained features. The output of the (conv5-block1-out) layer was flattened and connected to a series of fully connected (dense) layers to generate embedding vectors.
- **Trainable Layers:** While the majority of the ResNet50 layers were frozen, the final convolutional blocks were left trainable to allow fine-tuning during training. This ensures the model adapts to the domain-specific features of the dataset.
- **Triplet Loss [12]:** The network was trained using a triplet loss function, defined as:

$$L = max(0, D(a,p) - D(a,n) + \alpha) \tag{1}$$

  where: $D(a,p)$ is the embedding distance between the anchor (chipboard edge; a) and positive (matching edge band; p) embeddings. $D(a,n)$ is the embedding distance between the anchor and negative (non-matching edge band; n) embeddings. α is a margin parameter to enforce separation between positive and negative pairs. In other words to minimize the distance between the *Anchor* and the *Positive*, whilst maximizing the distance between the *Anchor* and the *Negative* using semi-hard batch mining technique applied in Schroff et al.'s study [12].
- **Embedding Vector:** The final dense layer produced an embedding vector for each input image, capturing the key features needed for similarity comparison.

D. Model Configuration

Two distinct models were developed to classify simple color-only decorations, and complex (colors and patterns) decorations, referred to as Model 1 and Model 2, respectively. As a result, if only color matching is important the model 1 is served, otherwise model 2 is considered.

Both models utilize the flattened output of the conv5-block1-out layer, which is subsequently connected to a fully connected layer. Model 1 employs dense layers with 512 neurons, while Model 2 utilizes dense layers with 256 neurons. Following this, each model is connected to an embedding layer. 4 nodes is used in Model 1 where 32 nodes is used in Model 2. A batch size of 64 is used for training, and the ReLU activation function is applied. The models are trained for 300 epochs in the case of Model 1 and 3000 epochs for Model 2. The triplet loss function is employed with a margin parameter α set to 0.1 for Model 1 and 0.3 for Model 2. Optimization is performed using the Adam optimizer with a learning rate of 0.0001.

V. Results

The performance of Model 1 and Model 2 are evaluated separately for clarity. For each model, 10% of the chipboards are used for test set and the remaining are used for training. All the relative edge bands are used for retrieval purpose.

TABLE I
THE MODELS RETRIEVAL RESULTS

k	Model 1	Model 2
5	50%	27%
20	77%	54%
50	84%	69%
100	95%	85%
200	100%	95%
250	100%	96%
300	100%	99%

As a result, for Model 1, 969 edge bands are evaluated for a matching chipboard, while 2466 edge bands are used for Model 2. The performance of the proposed models was evaluated using a precision-based metric. Specifically, for a given chipboard, the system ranks the top k most relevant edge band recommendations, and the expected band should ideally be included within these top k suggestions. This metric, which is known as *Top-k Accuracy*, reflects the model's ability to retrieve the correct match while minimizing manual effort in the selection process. Note that the problem is formulated as a retrieval problem. Complementary results such as F1-score or recall cannot provide valuable insight when the problem is formulated as a classification problem as there exist thousands of classes.

Two sets of experiments were conducted separately for the two models. The first column of Table I presents the results for Model 1, which is trained on simple bands where color similarity is the primary matching criterion. The second column of the table reports the results for Model 2, which is designed to handle complex decorations, incorporating both color and pattern similarity.

As observed in the results, Model 1 achieves higher precision than Model 2, which is expected given its focus on simpler bands with fewer distinguishing features beyond color. In contrast, Model 2 operates on more intricate patterns, making precise recommendations more challenging. Both models demonstrate strong retrieval performance. For the correct edge band being included 99% of the time, Model 2 requires the top 300 recommendations. Even though this many edge bands might seem large at first, this significantly reduces the manual search workload by approximately 91%, as the laborer only needs to inspect 300 options instead of manually reviewing 3,435 possible bands.

Note that, oftentimes the experts consider the provided candidates as good replacements and sometimes surprised to have a competing match to their labeled offerings. Qualitative observations suggest that in some cases, the models provide even more suitable recommendations than the actual target bands, indicating that the system can refine the selection process beyond traditional human decision-making. For example in Figure 7 the edge band `2669` is closer to the chipboard than the targeted `720` edge band. In Figure 6, although the targeted edge band is not retrieved in the top 5 best bands, the recommended edge bands are also quite suitable matches for the `1366` chipboard. This implies that the models' performance may be better than what is strictly reflected in the reported precision scores. By integrating this recommendation system into the workflow, workers can reduce manual errors, improve efficiency, and achieve higher-quality edge band matching results.

Another benefit of the proposed system is better inventory management. The manual edge band selection process requires an expert eye to go through thousands of candidates. Apart from being error-prone, even this simple search could take up to a few hours; therefore, it limits the production facility or the distributor to handle a few target chipboard designs per day. Moreover, if an existing matching edge band cannot be identified at that time, either a lengthy production pipeline must be initiated in vain, or an unnecessary order is placed to be delivered after some weeks.

Another utilization of the proposed system is preserving the uniformity of the product batches in time. A slight deviation might not be visible during continuous production. However, the proposed system could easily produce deviation scores from the approved initial sample.

VI. CONCLUSION

This study introduced a Siamese network-based approach for chipboard to edge band matching. The proposed model is an ensemble Siamese network-based approach that encompass both simple color-based bands and more complex, patterned designs. The proposed model demonstrated strong retrieval performance, with the correct band appearing in the top 300 recommendations 99% of the time, leading to an estimated 91% reduction in manual workload.

Beyond the reported precision scores, qualitative analysis suggests that the models can provide even better recommendations than the original target bands, highlighting their potential to enhance decision-making in industrial settings. By integrating this automated system, manufacturers can significantly reduce human errors, improve efficiency, and streamline the edge band selection process.

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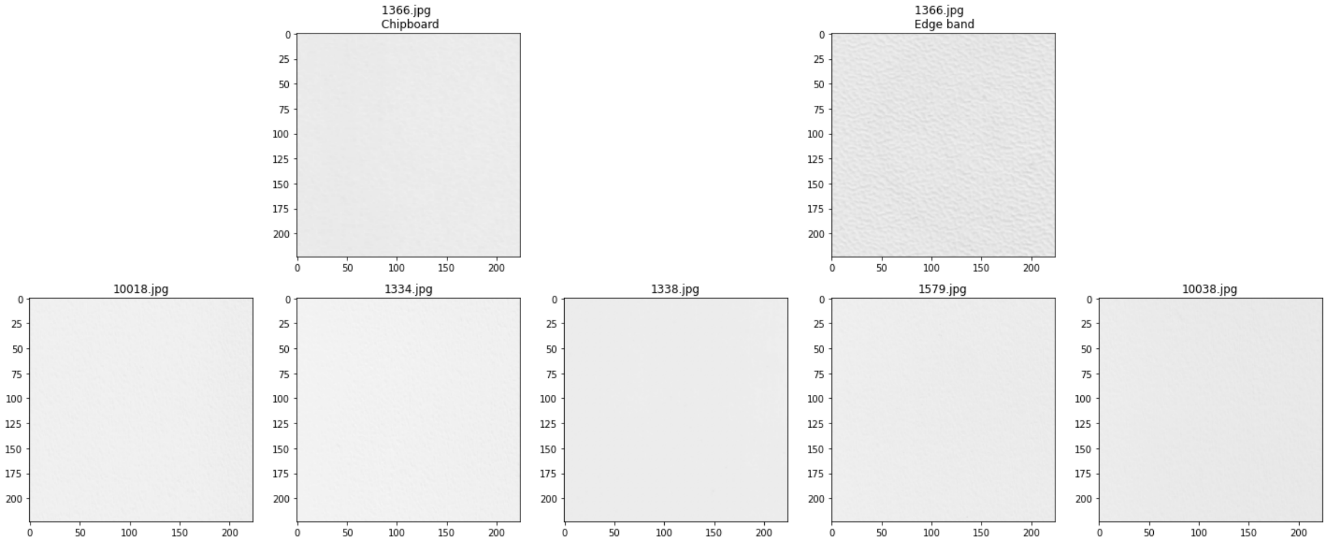

Fig. 6. Top 5 retrieved edge bands for chipboard 1366.

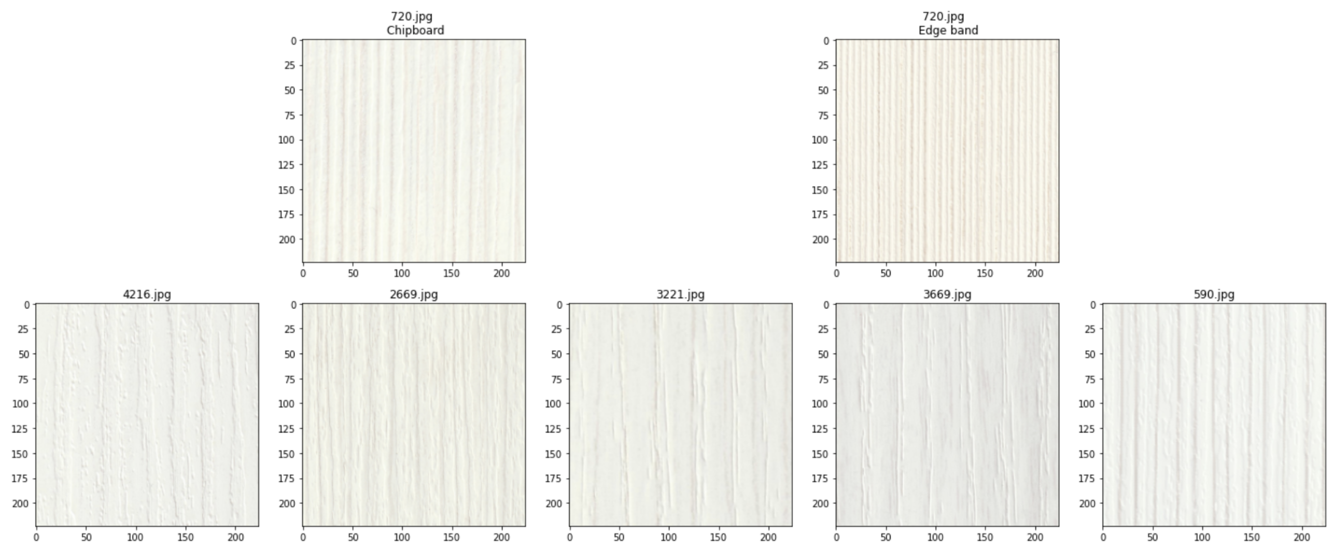

Fig. 7. Top 5 retrieved edge bands for chipboard 720.

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