Automated Defect Detection in Ceramic Tiles Using Transfer Learning Models

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Abstract: The ceramic tile enterprise is dealing with sizable challenges, particularly in growing countries with every everyday old technologies. The complex nature of the ceramic tile technology prepare often comes approximately in surface abandons inside the closing objects. Customarily, the class and reviewing of these gadgets rely upon human assessment, that can cause errors and irregularities. that is specifically concerning whilst tiles are utilized in legacy buildings just like the Taj Mahal, where defects could compromise such ancient structures' beauty and integrity. Therefore, it's miles essential to implement an automatic illness detection and type system to make sure that handiest tiles are used. in this paper, we recommend a version the usage of well-hooked up Convolutional Neural Networks (CNNs), which have been hired to discover and clas sify floor defects in ceramic tiles, attaining superior overall performance. Making use of those superior fashions ensures the tiles are very well inspected earlier than use, stopping any ability harm to crucial heritage web sites. The outcomes exhibit the effectiveness of this approach in surpassing present accuracy benchmarks, offering a reliable answer for the ceramic tile industry.

1 INTRODUCTION

In production, disorder detection is crucial for ensuring product quality and maintaining efficient manufacturing processes. Early detection allows for corrective actions, such as replacing machine tools or performing maintenance, to maintain process performance and reduce material waste. Defect detection typically precedes machine maintenance diagnostics and determines whether a product from a process or vendor should be accepted or rejected. Traditionally, this relied on manual inspection, but with increasing automation in manufacturing, automated defect detection systems have become essential.

One common approach involves analyzing is the surface images to identify defects. Widespread research has combined traditional image processing techniques such as edge detection, grayscale thresholding, and image segmentation defect patterns are continuous and contrast with the background. However, the ceramic tile industry, especially in developing countries faces challenges due to outdated technologies and reliance on manual inspection. Many manufacturers struggle with quality control, leading to manufacturers struggle with manufacturers struggle with quality control, leading to defective products and misclassified tiles. Worker fatigue and subjective judgment further exacerbate these issues. Addressing these challenges is critical to improving quality control and ensuring accurate defect detection, particularly in high-stakes applications like heritage sites and legacy buildings.

2 LITERATURE REVIEW

Image training is broadly applied for imperfection di scovery and type in a technology. Karimi and Asemani (Elbehiery, Hefnawy, et al. , 2007) remoted into four primary techniques to deformity place and type counting sifting techniques, basic calculations, version-based totally techniques, and authentic strategies. Having an area in the sifting method, neural systems are generally utilized (Wan, Fang, et al. , 2022). A. Tile floor Imperfection the invention of ceramic tiles is a important scholarly subject. numerous associated investigations have come about. Zhang et al. (Lu, Lin, et al. , 2022) outlined and in

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comparison, three discovery calculations, engaging in designed ceramic tile deformity department through threshold-based, flexible morphology, and wavelet exchange combination strategies. Zhang et al. (Hocenski, Vasilic, et al. , 2006) utilized the advanced SSR calculation, saliency discovery, and auxiliary place for complicated floor ceramic tile floor imperfection distinguishing proof. Casagrande et al. (Vasilic, Afshar, et al. , 2017) compared spotlight extraction techniques, deciding on fractal surface research and discrete wavelet trade, optimized parameters with a hereditary calculation, and utilized a classifier for deformity judgment. Haei S H et al. (Karimi, Mishra, et al. , 2024) utilized a nearby fluctuation rotation-invariant degree administrator for deformity facet extraction and bolster vector machines for imperfection type acknowledgment.

Those calculations are all based totally on preprocessing the image to kill commotion and at that point using pertinent administrators to extricate or improve imperfection area facts. those calculations have wonderful influences while there may be a self-obtrusive contrast among surrenders and foundation, however when the imperfection measure is little or there are expansive impedances with basis records, the impact can be destitute. at the equal time, these calculations as they were accomplish deformity sector extraction, whereas in real era, shifting ahead era productiveness by evaluating items agreeing to imperfection degree and amount is of extremely good significance et al. (Dong, Pan, et al. , 2024) proposed an unsupervised mastering-based surface imperfection discovery method, which utilized an autoencoder and clustering calculation to extricate and classify highlights from images, and at that point applied morphological operations and related space investigation to locate and fragment deformity areas. This method does not require categorized statistics, and might adaptively manage numerous kinds and surfaces of ceramic tile surfaces, but it could now not be capable of viably distinguish complicated and little abandons. Wang et al. show the N-DSCD calculation, which combines conventional location strategies with DCNN. This approach brings down untrue discovery rates and makes strides framework of common sense through a reference picture library and synchronized comparisons. In any case, keeping up an expansive reference picture library raises capacity and computational costs. Wan et al. proposed a profound learning strategy for ceramic tile surface deformity location based on an adjusted YOLOv5 arrangement and an information increase method. Their strategy can viably distinguish different sorts of abandons, such as splits, gaps, stains, and scratches, on distinctive sorts of tiles, such as coated, cleaned, and matte tiles. In any case, their strategy may not be able to handle complex and assorted foundations and may require more preparing information and computational assets. Hocenski et al.show an approach based on moving midpoints with nearby contrasts. It is able as it were to identify a constrained subset of blunders, those with tall differences to10the encompassing region of the tile. As a more common instrument for deformity location in ceramic tiles, a few FE strategies.

3 PROPOSED METHODOLOGY

In these works, we present a sensible defect detection system for the ceramic tile enterprise the usage of a hybrid deep gaining knowledge of version to pick out crack spots as defects at the manufacturing line. The version is trained the usage of 12,483 photos of ceramic tiles, with 9,988 snap shots used for validation and 2,495 photos used for education. We utilize three deep getting to know models: AlexNet, VGG16, and MobileNetV2, every contributing precise strength to improve crack detection accuracy. The AlexNet model consists of 5 convolutional layers, three max-pooling layers, 2 normalized layers, 2 fully connected layers, and 1 SoftMax layer. The convolutional layers are responsible for function extraction, where filters experiment the input snap shots to discover patterns together with cracks. each convolutional layer uses a ReLU (Rectified Linear Unit) activation feature, which introduces non-linearity to assist the version analyze complicated functions. The absolutely linked layers combine the extracted capabilities for type, with the SoftMax layer outputting whether a tile is faulty or not The VGG16 demonstrate, too referred to as VGGNet, is a 16-layer convolutional neural arrange that contains 13 convolutional layers and three absolutely related layers. Its deep structure and steady use of convolutional layers

make it distinctly effective for extracting relevant capabilities. MobileNetV2 a lightweight convolutional of the rectified system of the neural organize is specially mentioned for portable and implanted imaginative and prescient applications. It makes use of a green architecture with intensity-sensiable separable convolutions, which noably reduces the variety of parameters without compromising cracks in resource confined the time neural organize, is specially mentioned for portable and implanted imaginative and prescient applications.

It makes use of a green architecture with intensity-sensible separable convolutions, which notably reduces the variety of parameters without compromising accuracy. Fig[1] This makes MobileNetV2 ideal for real- time detection of defects, which includes cracks, in resource- confined environments like manufacturing traces. Its optimized design ensures that it can handle the demands of live defect detection. By leveraging the strengths of AlexNet, VGG16, and MobileNetV2 in a hybrid approach, the model enhances feature extraction and improves the accuracy of detecting cracks in ceramictiles. The hybrid method combines the best aspects of each model, ensuring high performance in the detection system. Moreover, transfer learning is used with pre- trained networks to enhance performance even more. This intelligent defect detection system contributes to improved quality control in the ceramic tile production process by reliably identifying defects like cracks in real time.

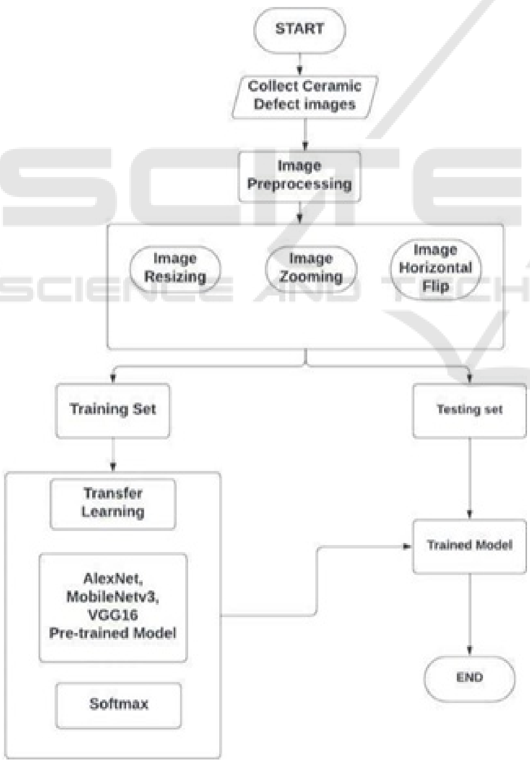

Figure 1: Architecture of Proposed Methodology

3.1 Common Surface Defects Of Ceramic Tiles

The ceramic tile manufacturing technique is intricate and involves a couple of degrees, every of which performs an important function in shaping the final product's fine. The stages regularly incorporate crude fabric arrangement, blending, crushing, shower drying, shaping, drying, coating, terminating, classification, and bundling. As ceramic tiles pass through these stages, there is a risk of defects emerging, particularly during sensitive processes like firing and glazing. Among the numerous defects that can appear, two are not ably common and significantly affect both the tile's structural integrity and aesthetic appeal:

3.1.1 Crack Defect

One of the most common and obvious flaws in ceramic tiles is cracking. These flaws show up as cracks or fissures that are evident on the tile's surface. Cracked tiles are generally considered unsuitable for sale and may need to be discarded or recycled.

3.1.2 Spot Imperfection

Spot imperfections refer to the presence of discoloured, uneven, or raised spots on the surface of ceramic tiles. Some spots may be small and blend in with the tile's pattern, while others can be large and starkly visible, making the tile unsuitable for high-quality finishes. Two common surface defects.

3.2 Image Augmentation And Preprocessing

In the context of detecting defects in ceramic tiles, image augmentation and preprocessing play vital roles in preparing high-quality images for training deep learning models. Here's how these processes are applied specifically to ceramic tile defect detection

3.2.1 Data Preprocessing

Image preprocessing ensures that all images used for training the model are clean, consistent, and ready for feature extraction. By improving the contrast of the pictures, histogram equalization makes flaws simpler to see and identify. These preprocessing steps improve the satisfactory of the input statistics, helping the model perform greater efficiently in figuring out tile defects in the course of production.

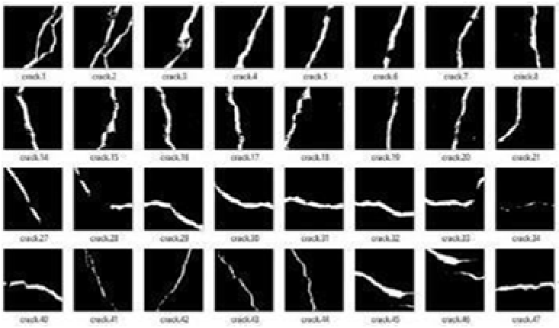

Figure 2: crack

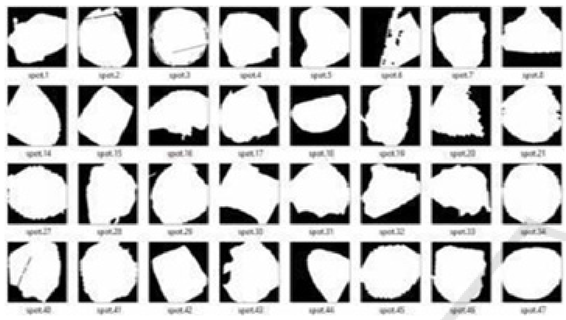

Figure 3: Spot

3.2.2 Data Augmentation

Image augmentation in ceramic tile defect detection involves transforming the original images to create a more diverse and comprehensive dataset. Translation shifts the image slightly, making the model robust to minor changes in tile positioning. Colour jittering introduces slight colour variations to mimic glazing inconsistencies, and adding noise to images teaches the model to focus on relevant defects rather than small artifacts or noise.

3.3 Adopting Transfer Learning Through Pre-Trained Network Models

After preprocessing highlights utilizing convolutional techniques, the precision of the models is thoroughly tried. To accomplish upgraded and exact comes approximately, the introductory show reviews pleasant- tuning via alternate studying. Exchange learning empowers integrating pre- trained thick neural arrange models, such as VGG-16, AlexNet, and MobileNetV2, with recently created models for successful extraction. This approach essentially decreases generalization blunders and streamlines the preprocessing of the dataset. In this work, the yield from a layer going before the last yield layer of the pre-trained organize is joined into the recently outlined profound learning show,workingas a modern coordinate including extractor. Sometime recently include extraction, the input picture tests must be resized to coordinate the required arrange of the pre- trained arrange models, particularly 224x224 pixels for VGG models. Once the highlights are extricated, the yield layer of the show identifies and classifies imperfect tiles, in this way calculating the misfortune and precision measurements. This setup encourages the real-time recognizable proof of inadequate tiles on the generation line, guaranteeing proficient quality control and improved operational viability in ceramic tile fabricating. MobileNetV2 is planned with a center on effectiveness and moo idleness, making it especially reasonable for inserted applications. Its design makes use of depth-clever distinguishable convolutions, which essentially decrease the number of parameters whereas retaining up tall precision in identifying surrenders along with breaks and notice defects in ceramic tiles. After resizing, the show extricates highlights from the pictures, and the yield layer classifies the tiles, calculating misfortune and exactness measurements to assess execution. For AlexNet, the resizing necessity remains steady at 224x224 pixels for input pictures. AlexNet's engineering comprises numerous convolutional layers that viably capture. Perplexing highlights from the tile pictures. The model's plan joins ReLU actuation capacities, pooling layers, and a SoftMax layer for classification, encouraging the location of abandons with tall accuracy. After highlight extraction, the yield layer recognizes and classifies imperfect tiles, computing the comparing misfortune and exactness measurements to screen the model's execution.

3.3.1 AlexNet

The layers that make up AlexNet are one SoftMax layer, 3 max-pooling layers, absolutely linked layers,5 convolution layers, and Normalized layers. The layers that make up AlexNet are one SoftMax layer, 3 max-pooling layers, two completely related layers, 5 convolution layers, and two Normalized layers. A non-linear activation characteristic called "ReLU" plus a convolution clear out make up each convolution layer. The max-pooling characteristic is executed with the aid of the pooling layers, and because absolutely linked layers are gift, the input length is fixed.

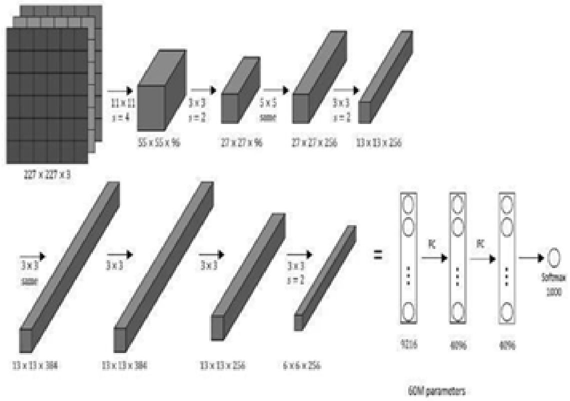

Figure 4: AlexNet Architecture

The architecture of AlexNet starts offevolved with an input photo size of 227x227x3. the primary layer is a convolutional layer with ninety six filters of length 11x11 and a stride of 4. The activation feature used on this layer is ReLU, generating an output feature map of 55x55x96. the subsequent layer applies max- pooling with a filter out size of 3x3 and a stride of 2, decreasing the function map to 27x27x96. Following applying 256 5x5 filters with a stride of one and ReLU activation to the pooling layer, the second one convolution operation is executed.The resulting feature map stays at 27x27x96. applying an additional max-pooling layer with a 3x3 filter out length and 2 stride outcomes in a characteristic map this is 13x13x256. using 384 3x3 filters, a stride of one, and ReLU activation, the 0.33 convolution layer generates a 13x13x384 characteristic map.the use of ReLU activation all over again, the fourth convolution operation preserves the 13x13x384 feature map length with 384 filters of size 3x3. the usage of 256 3x3 filters with a stride of 1 and ReLU activation, the fifth convolution layer a 13x13x256 function the subsequent of the primary layer due to

map A final max-pooling layer is then implemented with a filter length of 3x3 and a stride of 2, decreasing the feature map to 6x6x256. The output is flattened and processed via absolutely related (FC) layers following the convolutional and pooling layers. the first FC layer has 9216 units with ReLU activation, accompanied by using greater FC layers, each with 4096 devices and ReLU activations. The input picture is classified into considered one of one thousand categories the use of a softmax activation function inside the very last output layer, which has 1000 devices in overall.

- output= ((Input-filter size)/ stride)+1

3.3.2 VGG16

The convolutional neural community model known as the VGG model, or VGGNet, that helps 16 layers is also referred to as VGG16, together with 16 layers, which include thirteen convolutional layers and 3 fully linked layers. The VGG-sixteen is renowned for its effectiveness and ease of use, in addition to for its versatility in handling a range of computer imaginative and prescient programs, inclusive of object recognition. and image categorization. The model is designed with a series of convolutional layers followed via a stack of gradually deeper max-pooling layers.

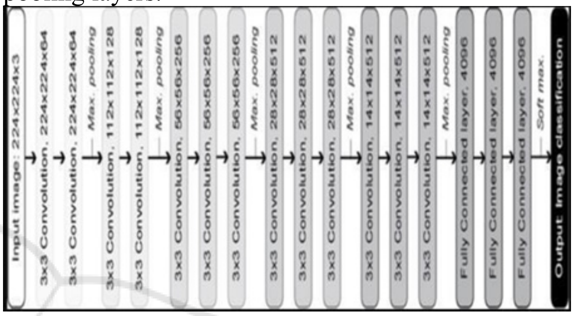

Figure 5: VGG16 Architecture

Images of 224x224 pixels can be entered into the VGGNet. To keep the enter size for the ImageNet opposition steady, the model creators eliminated the middle 224x224 patches from each picture. The convolutional regions of VGG use 33, the smallest workable receptive discipline, to seize motion from left to proper and as much as down. moreover, 11 convolution filters are used to transform the enter linearly. the following factor is a ReLU unit, an essential improvement past AlexNet that shortens training instances. The piecewise linear feature called the Rectified Linear Unit Activation function, or ReLU, outputs the enter if the enter is nice and returns zero in any other case. To hold the spatial resolution after convolution, the convolution stride—that's the quantity of pixels shifts over the input—is ready at 1. ReLU is activation function of the stride.

Utilized by the VGG community's hidden layers all.With VGG, neighborhood reaction normalization (LRN) is generally avoided because it lengthens schooling times and makes use of greater reminiscence. furthermore, it would not enhance accuracy overall.The VGGNet consists of three absolutely linked layers. while the 1/3 layer carries one thousand channels—one channel for every magnificence—the primary degrees each have 4096 channels.

3.3.3 MobileNetV2

A pre-educated version is a community it really is already been trained on a massive dataset and stored, which lets in you to use it to customise your model affordably and successfully. MobileNetV2, a lightweight convolutional neural community (CNN) architecture, is supposed often for embedded and cell vision packages. It turned into created by means of Google researchers as an improvement to the initial MobileNetV2 version. This model's ability to efficaciously balance model size and precision makes it best for gadgets with limited resources, that is another remarkable characteristic.

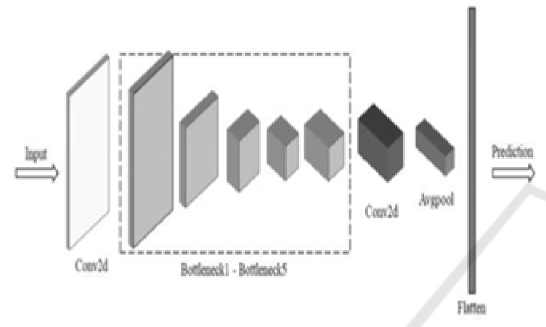

Figure 6. MobileNetV2 Architecture

The enter image length for the structure is 224x224x3 . the first layer is a convolutional layer with 32 filters of length 3x3 and a stride of one, producing an output characteristic map of 112x112x32 using the ReLU activation characteristic. this is followed by several bottleneck layers: the second layer has sixteen filters with a 1x1 kernel and a stride of two, lowering the function map length to 112x112x16. The third layer applies 24 filters with a 3x3 kernel and a stride of one, keeping the function map at 56x56x24, at the same

time as the fourth layer has 24 filters with a 3x3 kernel and a stride of 2, in addition decreasing the scale to 56x56x24. subsequent bottleneck layers continue this pattern: the fifth layer has 32 filters with a 3x3 kernel and a stride of 1 for an output of 28x28x32; the 6th and 7th layers practice 32 filters every with the same kernel length but extraordinary strides, resulting in a discount to 28x28x32. The 8th layer introduces 64 filters with a 3x3 kernel and a stride of one, generating a characteristic map of 14x14x64. Layers nine through eleven practice 64 filters every, maintaining the characteristic map length of 14x14x64. The 12th and 13th layers growth the filters to 96, keeping the dimensions at 14x14x96. The fourteenth and 15th layers follow 160 filters with a 3x3 kernel and a stride of 1, resulting in a function map of 7x7x160. in the 16th layer, 320 filters with a 1x1 kernel and a stride of one are employed. A final convolutional layer with 1280 filters and a 1x1 kernel produces an output feature map of 7x7x320. After this, a international common pooling layer reduces the characteristic map to 1x1x1280 earlier than the structure culminates in a completely related layer with a thousand devices and a softmax activation feature, classifying the enter image into one among one thousand categories.

- Algorithm for Testing Phase

4 RESULTS AND DISCUSSION

This section compares the suggested algorithm with current techniques and examines its performance over a range of training and testing data sizes. Accuracy measurements are computed once the performance metrics of the suggested method are assessed. The methodology's resilience and efficiency are showcased by the experimental findings, which show that it can attain an accuracy of up to 98.2% under ideal learning settings. Notably, the suggested methodology was applied with Jupyter Notebook and the Spyder IDE, utilizing key support libraries as Matplotlib, Scikit-learn, NumPy, Pandas, and Keras. The deep learning model's critical metrics, such as accuracy evaluation and loss metrics, were measured using the same tool chain. The result of with an astounding accuracy of 98.2%, MobileNetV2 proved to be the most effective model among those put to the test for spotting flaws in ceramic tiles.

5 CONCLUSION AND FUTURE WORK

This project demonstrates the potential of deep learning, specifically Convolutional Neural Networks (CNNs), in automating the defect detection and classification process in the ceramic tile industry. By employing advanced CNN architectures like AlexNet, MobileNetV2, and VGG16, the proposed system achieves high accuracy in identifying surface defects, outperforming traditional manual inspection methods. This automatic detection system can significantly reduce errors caused by human fatigue and subjective judgment, leading to better quality control, reduced waste, and more efficient production processes. Moreover, the system ensures that only high-quality ceramic tiles are used in critical applications, such as heritage and legacy buildings, where the aesthetic and structural integrity of the tiles is crucial. Moving forward, several improvements can be made to enhance the model's performance and scalability. First, integrating real-time defect detection in production environments can be explored, enabling manufacturers to make immediate corrective actions. Further optimization of the CNN model through hybrid techniques, such as combining genetic algorithms with CNNs, can lead to more precise results and faster computation. Additionally, expanding the dataset to include more diverse tile patterns and defect types will improve the model's robustness and generalization. Lastly, incorporating the system into a fully automated manufacturing line with real-time monitoring and feedback will help realize the full potential of Industry 4.0 in the ceramic tile sector.

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