



DETECTION OF DEFECTS IN CERAMIC TILES USING DEEP NEURAL NETWORK IN ARTIFICIAL INTELLIGENCE

S. Boovaneswari ^{1*}, S. Nirmal ², V. Meyappan ², B.Nandakumar ²

¹Assistant Professor, ²UG Student,
Department of Computer Science Engineering,
Manakula Vinayagar Institute of Technology, Puducherry

ABSTRACT: Quality control in ceramic tile manufacturing is hard, labor intensive and it is performed in a harsh industrial environment with noise, extreme temperature and humidity. It can be divided into color analysis, dimension verification, and surface defect detection, which is the main purpose of our work. Defects detection is still based on the judgment of human operators while most of the other manufacturing activities are automated so, our work is a quality control enhancement by integrating a visual control stage using image processing and morphological operation techniques before the packing operation to improve the homogeneity of batches received by final users.

1. INTRODUCTION

To keep their clients and to keep an upper hand in the worldwide market, manufacturing enterprises should maintain excellent guidelines. This requires the utilization of more compelling quality control methods and shrewd review conventions. Preceding being conveyed to the client; flawed items should be screened as a component of the quality control technique. Disappointment of the cycle would bring about long-lasting reputational harm and a decrease in corporate execution. A defect is a blemish in a delivered item's surface that often results from unavoidable, minute assembling process imperfections.

The fabric defects are broken filaments, slab, float, Gout, hole cut or ear oil stain. The name of the defects may vary from one material to another however the method to observe them remains the same, which is to look for irregularities on the surface. The process of quality control is vital for the positive outcome of any business. The Manufacturing industry, which knows about this, really focuses and consistently works on the foundation and activities for quality control to contend effectively with different areas. To achieve computer vision that is human-like, this includes using artificial intelligence (AI) effectively in the quality inspection process. Among different materials, the fabric defect detection turns into the famous subject because of the need of trustworthy and voluminous information examination prerequisite towards quality control in the material assembling industry. Since contrasting with different materials the Texture sees the boundless utilization in everyday premise.

Thus, even a miniscule deformity that can happen because of the mind-boggling producing process can't go on without serious consequences, since it can cause adverse consequence on business. Though a little imperfection might be remedied by talented laborers, A serious defect can deliver the fabric unsalable and subsequently makes misfortune income. Anyway, even the little defect ought to be recognized prior to sending the item to the market any other way it can make loss of reputation to the business. This makes the automated fabric inspection unavoidable. Anyway, there are difficulties that can radically diminishes the performance of the automation in the event that not considered during the beginning phases of calculation improvement. They are: (a) various classifications of fabrics (b) particular organization of different backdrop gatherings of texture surface, and (c) similarity in shape among defects. It isn't not difficult to handle every one of the difficulties by a solitary technique and expect to accomplish high recognition rate for a huge amount of tests from different gatherings

2. LITERATURE SURVEY

Ershad and Tajeripour (2012) had proposed customized surface variety from the standard area on 1D area equal models. The proposed approach is a two-phase process. First is a preparation step where defect less full surface pictures are changed over into 1D neighborhood twofold examples for working out essential component vectors. Progressively an edge is processed through noticing non-comparability between picture window and fundamental vectors. Second and last is a trying step which applies the figured defect less limit for identifying deserts on test pictures. The outcome examination shows the proposed strategy yields high recognition rate, and low computational intricacy.

Any texture is worked by redundancy of a unit design. Ngan and Ache (2009) by taking advantage of this example consistency nature have proposed a material examination procedure called Customary Band (RB). Initially in RB the properties of surfaces including distinguishing design and its routineness estimation prospects are presented. Next various customary philosophies, for instance, co-occasion organizations, autocorrelation, picture deduction and hash work are used to watch the periodicity and likeness of disfigurement free model plan against the surface picture. The presence of deformity makes the noticed surface picture unlike the example design subsequently summed up as defect. The result assessment shows the way that this approach can be associated for picture recuperation, picture mix, and for disfigurement place where plans are clearly portrayed.

Location of defects and arrangement of artistic tile surface deformities occurred in terminating units are normally finished by human perceptions in many production lines. In this paper, a programmed picture handling framework with high sureness and time effective methodologies is shown. To this end, first, for defect location, Revolution Invariant Proportion of Nearby Fluctuation (RIMLV) administrator from factual procedure is utilized for deformity edges identification, and helpfully a Nearby morphological administrator from primary strategies is utilized to fill and smooth recognized districts. Then, at that point, every one of the identified defects of one earthenware tile are assigned, and the comparing mathematical highlights are acquired. At long last, a multi-class support vector machine classifier with champ brings home all the glory technique in view of factual example acknowledgment speculations is utilized to

look at the deformity type. During Artistic Tile production (CT), many defects will have happened over coat terminating stage in furnace, and one of the normal blemishes is surface deformities. These defects for the most part have different visual examples which are at times conflicting or unapparent. In any case, as of late, CT enterprises incorporate various state of the art techniques of creation and computerization albeit human administrator is as yet utilized to identify deserted CTs and evaluating in many outlets such countless blunders happen because of beginning, for example, CT exclusion and natural defects such being languid. As needs be, a programmed discovery and arrangement framework should be substitute in compelling, level headed, rehashed and fast way. High exactness of this framework is basically useful to control of terminating oven factors as a picture criticism, which brings about a significant improvement in quality control (QC). Different handling calculations have been submitted for programmed deformity location and order, two principal phases of this framework. In this paper, to plan a programmed identification and arrangement set, above all else, Revolution Invariant proportion of Neighborhood Difference (RIMLV) administrator from sub-classifications of factual methodologies, acquainted by Ojala is utilized with deformities' edge discovery.

To explain the issue of bogus defect recognition of the surface trait of fired tiles, complex-finished artistic tiles is proposed. In light of the visual recognition rule of ceramic tile surfaces, a picture procurement framework is settled to acquire the ceramic tile picture. After picture division and reevaluation, the surface deformities are essentially recognized utilizing a saliency discovery technique. Saliency Discovery is animating move toward PC vision which targets tracking down critical article.

Programmed surrenders review and order in ceramic tile assumes a critical part in clay tiles industry. To further develop the normal registering time to distinguish and isolate spot and break deserts in fired tiles, this paper plotted equal calculations in view of the graphical handling unit. The ceramic tile pictures are isolated by following proposed calculation into non-covered parts, distinguishes the deserted segments and afterward does the deformity characterization calculation just on the abandoned parts. Reenactment results show huge upgrades as far as characterization time in contrast with the ongoing methods. Besides, calculation time for equal calculation succeeds the consecutive calculation. The outcomes show the accelerate of the calculation of the conspired equal dissected with sentential calculations that increment as the picture size increments.

It is utilized to sort out strings in 2D lattice and blocks where each block has 16×16 number of strings and matrix determine with 50×50 number of blocks when picture size 790×779 . The quantity of blocks produced in the lattice differed by the picture size. So, for every passage in the picture, there is just a single string is utilized to deal with the pixel. The code of the 2D-Portion answer for discovery calculation and string association is created without dividing the artistic tile picture. As such, in this arrangement all picture sections are handled during identification and order calculations. It is utilized to arrange strings in 1D framework block. This association of strings is utilized to parcel the picture into non-covered parts. In this way to foster the proposed equal defect recognition and characterization calculation, the string

association is changed from 2D to 1D. It is carried out by separating the picture into various segments in the Portion capability. Thusly, the allotments will be checked the deformity found or not so much for everyone. When a surrendered block is recognized, the calculation groups the kind of the defect in equal. Consequently, the earthenware picture is separated in view of the quantity of the blocks in the network. The motivations to involve fixed number of blocks in this task are as per the following. First is to decrease the quantity of tasks. Second the piece capability allows a particular number of boundaries. Third, to diminish the above of moving information from/to central processor to/from GPU. Also, to decrease the expected chance to separate the earthenware picture into allotments this undertaking limit the quantity of blocks in as far as possible to six blocks.

The recognition calculation which is having a low exactness is one hindrance in identifying ceramic tile's surface deformities web-based focusing on wise identification rather than human review. The reason for this paper is to introduce a CNFA for tackling the block. For the most part, a negative example set is created web-based by non-flawed pictures of ceramic tiles, and a comparator in light of a changed VGG16 separates a reference picture from it. Camouflaged square shape boxes, including imperfect and non-deficient, are caught from the picture to be supported by a locator. A reference square shape box is generally like the hidden square shape box which is separated from the reference picture. A discriminator is comprised with an altered MobileNetV3 network which fills in as the spine and a measurement learning misfortune capability which fortifies highlight acknowledgment, separating the valid and bogus of changed and reference square shape boxes. Results display that the discriminator seems to have an exactness of 98%, 13% more than different calculations. Besides, the CNFA plays out a normal precision of 98%, and the consuming season of a solitary picture reaches out by just 64.35ms, which has little effect on creation proficiency. Surface deformity location of items which gives a hypothetical and functional reference for with perplexing and variable surfaces in modern conditions.

The dim line indicates that a picture to be distinguished is straightforwardly induced, and databoxes encompassed by the light orange foundation box are acquired at the same time by the indicator. The blue line demonstrates the comparator extricates include vectors of non-deficient and imperfect pictures, then, at that point, the most comparable non-blemished picture recovered is the reference picture, ref_boxes encompassed by a light green foundation box are procured in view of the reference picture and det_boxes. Inferable from foster the exactness of surface defect discovery for CT, this paper presents a calculation that joins connection, identification, and separation. The finder designs the defect location execution of the CNFA. Working on the finder's aversion to deformities will convey a high misleading discovery rate, which is unsuitable in functional applications. Likewise, the proficiency of this proposed still up in the air by the comparator and the discriminator together. The comparator is utilized to remove the qualities and examine the picture to be identified with the negative example set, and eventually the relating reference picture is gotten.

The finder gets a handle on the deformity target identification on the recognized picture to secure square shape boxes; the discriminator all the while achieves include extraction and

likeness estimations of the got rectangular boxes from the reference picture and the one to be uncovered, at last looking at whether the square shape boxes of the picture to be distinguished are genuine defects. The whole methodology process comprises of the accompanying advances: 1) Gathering non-blemished tile pictures of differentiating surfaces. 2)The comparator is first used to pith the component vectors of the recognition picture, named V_{det} (β_i). 3)The classification and square shape boxes of the picture to be identified are gotten by the defect identifier, and the square shape boxes picture are abbreviated. 4)The det boxes and the relating ref boxes are coordinated into the discriminator; 5) The judgment of the valid/misleading deformity of the det boxes is achieved by the limit. Clean fired items, like latrine and wash bowl, are broadly utilized in our everyday existence. Sterile earthenware production are supposed to have a few superb actual properties, like consumption opposition, simple cleaning, and low water ingestion. Be that as it may, surface defects in sterile ceramics are unavoidable because of mind boggling creation processes and changing creation climate. In this manner, surface defect location should be acted in the assembling system of clean earthenware production. There are many kinds of surface deformities in sterile earthenware production, and various sorts of defects have enormous contrasts in attributes and scales. Conventional discovery techniques with misleadingly planned highlights and classifiers are challenging to apply in this unique circumstance. Moreover, there are not many investigations on surface defect identification techniques for clean ceramics in light of profound brain organizations. In this article, a lightweight constant defect location network in view of the lightweight spine MobileNetV3 is introduced. The proposed network accomplishes multi-scale location of surface defects in sterile earthenware production with a multi-facet highlight pyramid. Joining area proposition organization and sans anchor strategy, continuous defect discovery is accomplished. At long last, a discovery head with station consideration structure and a low-level blended include order procedure is utilized to perform defect characterization with higher precision. Exploratory outcomes show that the proposed approach accomplishes somewhere around 22.9% identification speed improvement and 35.0% normal accuracy improvement while decreasing memory utilization by no less than 8.4% contrasted and the exemplary one-stage SSD, Just go for it V3 and two-stage Quicker R-CNN techniques.

3. EXISTING SYSTEM

Fabric manufacturing Process

Normally textures are made with material strands. The material filaments can be made of characteristic component, for example, cotton or fleece; or a composite of various components, for example, fleece and nylon or polyester

Fabric production is usually achieved in few basic steps. The first step is yarn production. It involves set of process that converts the raw fibers into yarn and threads. This requires spinning the fibers either by hand or by spinning wheel. Winding is the last step in spinning process. Winding 74 process involves transfer of spinning yarn from one package to another large package. In next step these individual threads are joined together by a process called weaving to form fabric. The woven fabric is discolored and full of impurities. Therefore, it is treated with bleach and other chemicals to remove oils, wax and other impurities.

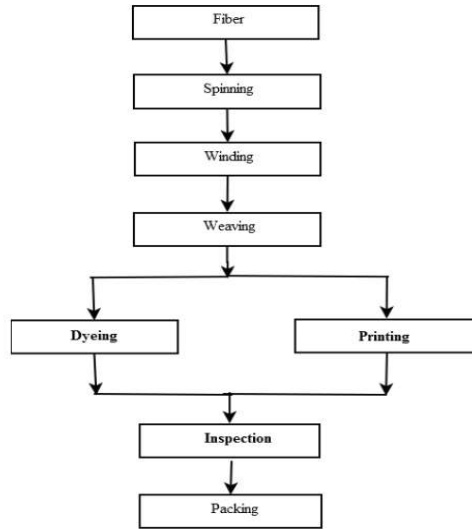


Figure 4.1 General Workflow of manufacturing process in Textile Industries

Dyeing and printing are crucial processes that are required for converting raw textile into finished fabric with desired appearance. Both as a wet processing technique used for coloration of fabric. Single color and grey fabric are often involved in Dyeing. Whereas multiple color and both 76 pre-treated and colored fabric are involved in printing process Dhivya & Devi et al (2017).

Whether a fabric is dyed or printed it can be easily distinguished by looking at the outline of the design. In printed fabric the design outline is sharp but does not penetrate to the other side. The following are some of the examples of fabrics.



Figure 4.2 Various types of fabrics

Classification of Fabric Defects

The defect is the common term in the garment industry. Since the defect in garment industry is identified as reject item. In India such defective garments are sold in subsidized cheap rates during a month. However, in textile industries different four types of defects are identified and specified for better inspection process as listed in Table

Table 4.1 Types of Fabric Defects

Yarn Defects	Woven Defects	Knitted Defects	Dyeing Defects & Finishing Defects
Broken Filaments	Broken Ends	Drop Stitches	Shade Variation
Knots	Float	Yarn Streaks	Crease Mark
Slub	Gout	Barriness	Pin Hole Damage
Fabric press off	Hole, Cut or Tear	Fabric press off	Dye Spots
Broken Ends	Oil Stain	Broken Ends	Wrong Slitting
Thick places	Slub	Spirality	Band Line

Thin places	Missing end	Slub	Dust
	Reed Mark	Broken Needle	
	Colour Bleeding	Cracks or Holes	
	Missing Picks	Pin Hole	

Any defect in a fabric or textile can be identified as a variation from the usual appearance Gaidhani et al (2014). Texture defects can occur in non-textured areas or areas that locally differ from the background texture of the surface.

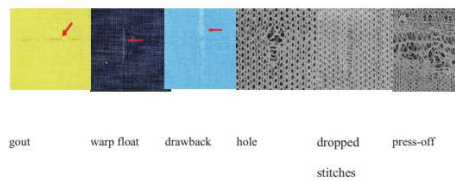


Figure 4.3 Samples of commonly occurring fabric defects

The figure shows the rundown of ordinarily happening texture surrenders. The anticipated deformities ordinarily happen because of machine deficiencies, yarn issues, poor completing, and over the top extending. Gout is a knotty and unbalanced blame in a spun yarn of a texture 79 which happens amid turning. Twist skim is a length of yarn that is unbound more than at least two progressive closures or singles out the twist heading. Downside is a weave contortion described by tight and slack places in a similar twist yarn. Hole or tear simply mean a small hole in the fabric. Dropped stitches are irregularities in yarning or stitching patterns. Press-off occurs accidentally with yarn breakage Gaidhani et al (2014).

Critical Defects

If a defect is likely to results in hazardous conditions or unsafe for usage, then it is considered as critical defect. It is simply a huge deviation from delivery requirements and the product cannot be delivered to the customer at all. Usually, the entire lot is rejected under the finding of even a single critical defect during inspection Shweta & Dhirendra et al (2015).

Minor Defects

A minor imperfection is a slight deviation from the conveyance necessity and is probably not

going to bring about client protestation or return. However, a defect is a defect, if many manufactured products exhibit minor defects, then it will definitely cause the product rating to go down and thus affects the business. A minor defect is often overlooked by the inspection process and still remains a huge challenge Shweta & Dharendra et al (2015).

Consequently, the size of the defect is a huge problem when it comes to defect detection. Minute defects are elusive and are hard to detect through expert inspection as well as for automatic detections. The methods which work with well-defined defect specification may be fooled by such 81 possibility Minal et al (2017). Most of the computerized inspection techniques draw inspiration from pixel-wise defect labeling. However, the surface inspection using fabric texture surface image defers significantly from general texture segmentation and classification, since the surface image and the defects are highly stationary. The challenge is to segment the surface image into smaller regions to locate the defects. The challenge is to bring a defect within the segment if the defective region is split the defect detection results in poor performance. Moreover, defects may not always fall within the trained defect sample class. Therefore, to understand the computer vision-based texture defect detection application, the fundamental operations that serves as the core requirement is discussed in following section.

Distinguished Characteristics of Texture Defect Detection

The texture defect detection algorithm as an extension of pattern recognition application accepts the fabric surface image as input. Subsequently runs the algorithm which is trained with the samples of defect-less surface image. Since most of the fabric defect detection classifiers are trained with texture-based samples, they tries to detect defects 82 and returns a binary (black & white) image. Where white denote the texture defects. The following set of images shows the input images and its corresponding output below it.

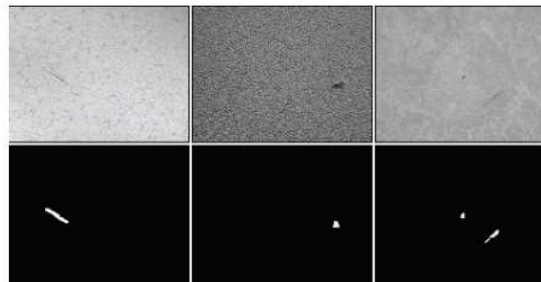


Figure 4.4 Input surface images with defect in 1st row and it's output in 2nd row

This defect detection application however is capacitated with certain user-friendly characteristics. They are as follows,

Scale Variation Improvisation

The automatic adaptation feature of various defect detection classifiers makes them naturally capable to adjust to scale variation of approximately ± 10 degrees. However, if the defect inspection is expected to scale for 84 further variations, then it must be improvised with the samples for each and every scale variation Karolina et al (2013). The following figures

illustrate a difference in scale that requires trained samples for each variation.

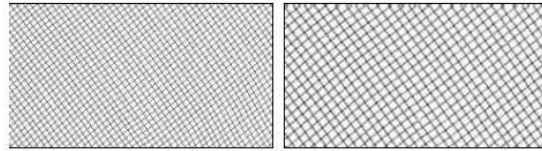


Figure 4.5 Depicts the categories of scale variations

Sequence of steps in Automation

Image acquisition:

The CCD (charge-coupled device) camera or a CMOS (complementary metal - oxide semiconductor) camera and a frame grabber is usually used for image acquisition process Gonzalez & Woods (2008) Kumar et al (2001). Moreover, the resolution is a crucial factor for performing effective defect detection Shweta & Dhirendra et al (2015). Consequently, for industry standard applications the high-resolution camera is used to detect all the possible defects even though it adversely affects the inspection speed.

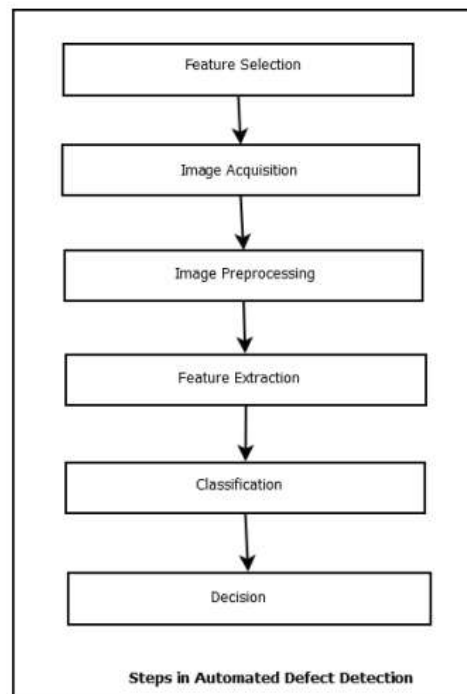


Figure 4.6 Basic Steps in Defect Detection Automation Process

4. PROPOSED WORK

Detection method for the surface defects of complex-textured ceramic tiles was studied. After tile image acquisition and preprocessing, the defects were detected using the saliency

detection method and then a defect determination model was established to detect the error of defect areas to eliminate the false defects. The main conclusions are as follows.

An image acquisition system of the ceramic tile surface is established. Image segmentation is completed by determining the four vertices of the ceramic tile, and illumination correction is performed using an improved SSR algorithm.

The Color spatial distribution variance (CSDA) feature and Color spot area weight (CSAW) feature are used to obtain the saliency map; the maps are fused in the exponential form, and the defect saliency map is achieved.

A model for determining the correctness of ceramic tile surface defects is established. The optimal parameters of the model are obtained via the grid search.

The feasibility and effectiveness of the proposed method are verified via comparative

Disadvantages of Existing System

However, because of special shape and structure, there are some limitations of using different methods of machine vision for shape, texture and color detection, then recognition of and Crack.

Computation time is very large as percolation process starts from each pixel and huge computation power is also needed.

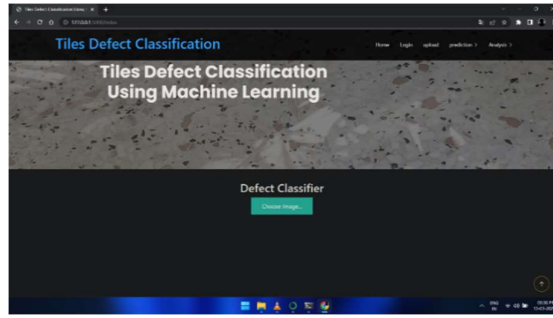
Still, many irrelevant objects are misidentified as cracks.

Objective

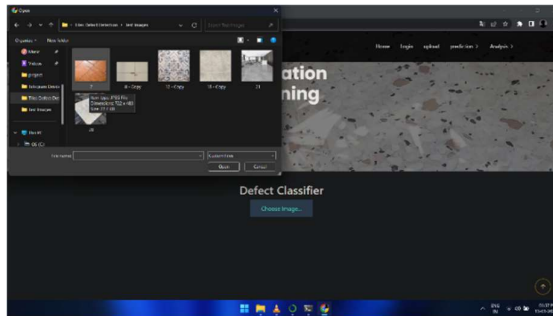
This long-term research objective contributes to advancements in the design of robust low-cost intelligent systems for real-time inspection of smooth specular coatings. In this investigation, the primary defects studied are seed defects and spot defects. This is because they are the common surface defects found on real ceramic tiles and present as irregular shapes and different sizes. Image processing algorithms for defect detection and feature extraction are proposed and executed on a group of smart cameras using their on-board processing ability. Finally, an integrated small-scale low-cost experimental test bed is developed for the real-time implementation of proposed algorithm

5. IMPLEMENTATION

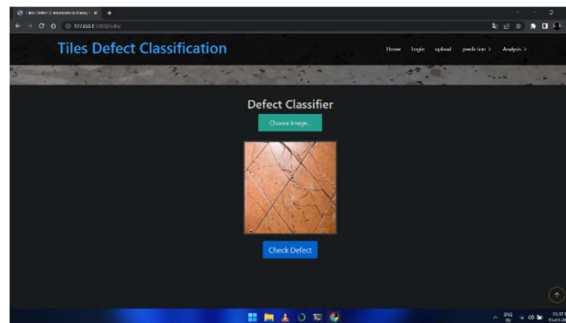
When an image of a tile is uploaded to a website for evaluation, an automated system performs a comprehensive analysis to assess its quality and condition. The system employs advanced algorithms to examine various aspects of the tile's appearance and structure. It evaluates factors such as color consistency, surface texture, pattern integrity, and edge alignment to determine if the tile exhibits signs of aging, defects, or damage. By scrutinizing these visual characteristics, the system provides users with valuable insights into the condition of the tile. This process enables users to make informed decisions about whether the tile meets their requirements without the need for physical inspection. The automated evaluation system streamlines the tile selection process, saving time and effort while ensuring accurate assessments of tile quality.



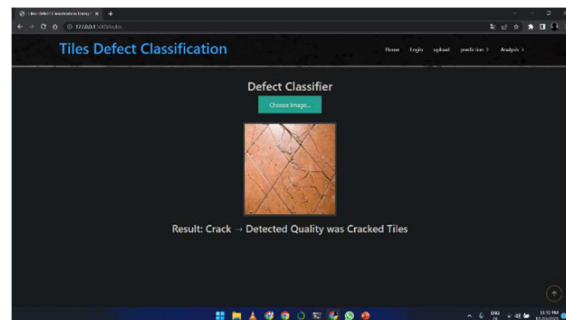
Step1: Opening the website for tiles Detection



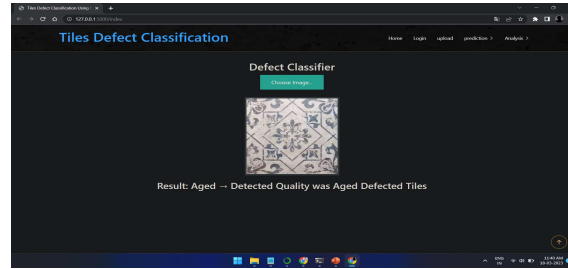
Step2: Selecting the tiles image and uploading



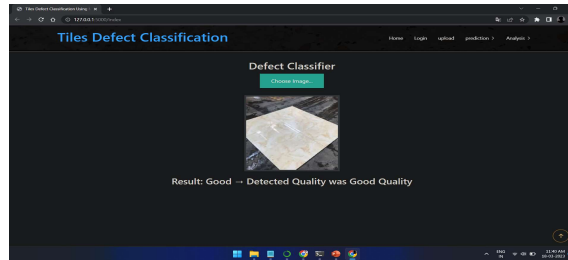
Step3: Checking the Image



Step4: Result as Cracked Tiles



Step4: Result as Aged Tiles



Step4: Result as Good Tiles

6. CONCLUSION

The SVM assume a significant part to characterize the defect for Quality control framework in material industry. Anyway, the productivity of the current way to deal with classify the surface deformity is exceptionally low. Portion as its functioning standard can plan information to higher request and higher aspects until it becomes straight example reasonable to apply direct model. Hence an original ISVM with improved part capability for picture characterization and for division, MFCM has been proposed to order and distinguish deserts with higher precision. By consolidating and using the two bits to distinguish the hyper plane improved results were accomplished. The proposed calculation has been tried against the current strategy for boundaries like responsiveness, particularity and exactness. The outcomes show that the proposed calculation performs really and sums up additional deformities than existing techniques. This examination work thoroughly searched in to different parts of Surface deformity recognition and offered a complete and practical way to deal with support the quality control process in limited scope and medium scale Material businesses. Anyway, the model can be appropriate to all informational indexes in term of tiles, steel, stones and any example surface picture and so forth continuously stages. Seriously testing will offer fascinating aspects in light of the fact that the proposed approach is tried with industry & bench mark informational indexes accessible surface picture datasets in view of industry grade picture scanner. This has definitely affected on responsiveness measures. Notwithstanding, checking the proposed calculation with discoveries speed with very good quality camera in industry level activity can assist with improving the presentation. For example, the ongoing testing will give bits of knowledge upon the information varieties, for example, pivot and scale variety that might occur in normal working foundation of cost constrained limited scope businesses. This will then, at that point, help to improve the self-adaptability qualities of the proposed system with important

changes.

7. REFERENCE

1. Bounegru L, Gray J, Venturini T, Mauri M. A Field Guide to 'Fake News' and Other Information Disorders. A Field Guide to " Fake News" and Other Information Disorders: A Collection of Recipes for Those Who Love to Cook with Digital Methods, Public Data Lab, Amsterdam (2018). 2018.
2. Shrivastava, G., Kumar, P., Ojha, R. P., Srivastava, P. K., Mohan, S., & Srivastava, G. (2020). Defensive modeling of fake news through online social networks. *IEEE Transactions on Computational Social Systems*, 7(5), 1159-1167.
3. Kumar, A., Nayak, S., & Chandra, N.: Empirical Analysis of Supervised Machine Learning Techniques for Cyberbullying Detection. In: International Conference on Innovative Computing and Communications, pp. 223-230. Springer, Singapore (2019).
4. Mladenović, M., Ošmjanski, V., & Stanković, S. V. (2021). Cyber-aggression, cyberbullying, and cyber-grooming: a survey and research challenges. *ACM Computing Surveys (CSUR)*, 54(1), 1-42.
5. Kumar, A., & Jaiswal, A. (2019). Swarm intelligence based optimal feature selection for enhanced predictive sentiment accuracy on twitter. *Multimedia Tools and Applications*, 78(20), 29529-29553.
6. VanHee, C., Jacobs, G., Emmery, C., Desmet, B., Lefever, E., Verhoeven, B., ... & Hoste, V. (2018). Automatic detection of cyberbullying in social media text. *PloS one*, 13(10), e0203794.
7. Hang, O. C., & Dahlan, H. M. (2019, December). Cyberbullying lexicon for social media. In 2019 6th International Conference on Research and Innovation in Information Systems (ICRIIS) (pp. 1-6). IEEE.
8. Young, T., Hazarika, D., Poria, S., & Cambria, E. (2018). Recent trends in deep learning based natural language processing. *IEEE Computational Intelligence Magazine*, 13(3), 55-75.
9. Ballal N., Saritha S.K. (2020) A Study of Deep Learning in Text Analytics. In: Shukla R., Agrawal J., Sharma S., Chaudhari N., Shukla K. (eds) Social Networking and Computational Intelligence. Lecture Notes in Networks and Systems, vol 100. Springer, Singapore. https://doi.org/10.1007/978-981-15-2071-6_16
10. Kumar, A., Srinivasan, K., Cheng, W. H., & Zomaya, A. Y. (2020). Hybrid context enriched deep learning model for fine-grained sentiment analysis in textual and visual semiotic modality social data. *Information Processing & Management*, 57(1), 102141.
11. Kumar, A., & Jaiswal, A. (2020). A Deep Swarm-Optimized Model for Leveraging Industrial Data Analytics in Cognitive Manufacturing. *IEEE Transactions on Industrial Informatics*, 17(4), 2938-2946.
12. Kumar, A., & Jaiswal, A. (2020). Systematic literature review of sentiment analysis on Twitter using soft computing techniques. *Concurrency and Computation: Practice and Experience*, 32(1), e5107.
13. Sangwan, S. R., & Bhatia, M. P. S. (2020). D-BullyRumbler: a

safety rumble strip to resolve online denigration bullying using a hybrid filter-wrapper approach. Multimedia Systems, 1-17.

13. Brown, L. (2012). New Harvard Study Shows Why social media Is So Addictive for Many. [online] WTWH Marketing Lab. Available at: <http://marketing.wtwhmedia.com/new-harvard-study-shows-why-socialmedia-is-so-addictive-for-many/> [Accessed 27 Jan. 2020].

14. <https://coschedule.com/> Accessed on 14 July 2018.