A COMPREHENSIVE REVIEW ON STATE-OF-THE-ART IMAGE INPAINTING TECHNIQUES

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Abstract. Image inpainting is the process of restoring missing pixels in digital images in a plausible way. A study on image inpainting technique has acquired a significant consideration in various regions, i.e. restoring the damaged and old documents, elimination of unwanted objects, cinematography, retouch applications, etc. Even though, limitations exist in the recovery process due to the establishment of certain artifacts in the restored image areas. To rectify these issues, more and more techniques have been established by different authors. This survey makes a critical analysis of diverse techniques regarding various image inpainting schemes. This paper goes under (i) Analyzing various image inpainting techniques that are contributed in different papers; (ii) Makes the comprehensive study regarding the performance measures and the corresponding maximum achievements in each contribution; (iii) Analytical review concerning the chronological review and various tools exploited in each of the reviewed works. Finally, the survey extends with the determination of various research issues and gaps that might be useful for the researchers to promote improved future works on image inpainting schemes.

Key words: Image inpainting; Region Filling; Performance Measures; Chronological review; Tools; Research Gaps.

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1. Introduction. "Inpainting refers to the art of restoring lost parts of the image and reconstructing them based on the background information, i.e. image inpainting is the process of reconstructing lost or deteriorated parts of images using information from surrounding areas" [66, 67, 68, 91]. It comprised of tasks like object disocclusion, filling holes and image restoration, etc. At first, the theory of digital inpainting was established by Bertalmio et al [90]. According to this technique, higher-order PDE was exploited for restoring purposes. Here, the areas to be filled are based on the assistance of gradient direction. The two most important classification of inpainting consists of textural and structural inpainting [69, 70, 71].

The regions outside the area to be inpainted are modelled by the texture inpainting approaches [72]. This was exploited to the textures with randomized 2D models. Consequently, the structural inpainting schemes attempt to rebuild the structures such as object and line contours. Usually, structural inpainting is deployed when the portion to be inpainted is small [73, 74, 92, 93]. It concerns on linear structures that could be considered as 1D pattern such as object and line contours. Moreover, image compression could be done effectively by neglecting certain portions at the encoder side and inpainting those portions by a similar technique at the decoder side [75, 94].

Also, morphological processes namely corrosion could be exploited for inpainting the smaller portions of missing values. In fine painting museums, inpainting of corrupted painting were usually done by skilled artists and generally, it is found to be much time-consuming. There were numerous techniques implemented for image inpainting [76, 77, 78]. "Microsoft Kinect sensor" is an inexpensive device, which has influenced a lot of analysts to handle with deep data. However, issues exist with this device in terms of its resolution and accuracy [79, 80, 81].

The main contribution of this paper is depicted below:

1. This work conducts a survey of diverse techniques related to various image inpainting schemes that are contributed to each paper.

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2. Accordingly, the performance measures and the corresponding maximum achievements are also investigated.

3. Furthermore, various tools exploited in each work are reviewed and a chronological analysis is also made.

4. At last, the research challenges and gaps on image inpainting systems are also exhibited.

The paper is prearranged as follows. Section 2 portrays the related works and section 3 presents a comprehensive review of adopted algorithms, performance measures, as well as the maximum achievements and Section 4 describes the assessment on adopted tools and chronological review in each work. Moreover, Section 5 elaborates on the research gaps and challenges, and Section 6 concludes the paper.

2. Literature review.

2.1. Related works. In 2014, He et al. [1] have presented a novel wavelet frame oriented weight minimization approach for inpainting the image. Numerical analyses have revealed the significances of the presented scheme in conserving the image edges. In 2016, Chen et al. [2] have presented a scheme using PPA for resolving the issues in non-orthogonal wavelet inpainting. Mathematical analyses have shown the superiority of the presented approach over the compared models in terms of performance time. In 2017, Chen et al. [3] have proposed a novel scheme that exploited the Patch priority algorithm for covering up the required data that ensured the configuration stability. In the end, simulations were held and the outcomes have demonstrated the effectiveness of this method.

In 2017, Fei et al. [4] have implemented a paper depending on the ADMM) technique. In the end, mathematical analyses have shown that the presented scheme was capable of attaining considerable computational gain. In 2017, Xue et al. [5] have introduced a technique using the "Low gradient regularization" model, by which the penalty for small gradients was reduced. Also, the investigational results have shown the efficacy of the implemented model. Vahid et al. [6] have presented a novel technique that deployed the Orientation matrix model for non-textured inpainting of images. The presented approach was further deployed for better and faster inpainting.

In 2017, Wang et al. [7] have developed the space varying updating approach for enhancing the priority evaluation. Also, FFT was deployed that searched the whole image and provided quicker matching outcomes. Finally, the outcome shows the enhancements made by the implemented technique. In 2017, Ying et al. [8] have established an image inpainting scheme, which comprised of the PSNR values for enhancement. The analysis outcomes have shown that the presented method attains better PSNR value over other compared schemes. In 2007, Ubirat et al. [9] have introduced the concept for block-oriented image inpainting in the wavelet domain. In the end, simulations were held that proved the efficiency of the presented scheme in filling the areas with better visual quality.

In 2016, Barbu et al. [10] have exploited the variational model for image reconstruction, which depended on 2nd-order PDE. Certain successful image inpainting analysis and evaluation were also explained in this work. In 2016, Muddala et al. [11] have suggested an LDI, which aimed at enhancing the rendering quality of the images. As per the subjective and objective assessments, the developed technique outperformed the conventional schemes at the disocclusion. In 2012, Arnav et al. [12] have presented a scheme that prevailed over the drawbacks of low-resolution issues that resulted in poor occlusions. The experimental analysis illustrated that the presented model could efficiently reconstruct the images with reduced noise.

In 2012, Dhiyanesh and Sathiyapriya [13] have analyzed the active snake model for image segmentation. The experimentation illustrated that the presented method offers better outcomes over the other conventional methods. In 2013, Wang et al. [14] have introduced an effective transform-oriented approach for geometric techniques that tackled over the reduced efficiency. Further, the investigational analysis demonstrated that the adopted technique enhances and speeds up the performances along with improved restoration outcomes. In 2012, Li and Yan [15] have developed a novel approach, which was dependent on the TV approach. From the analysis, a reduced computational time was achieved by the presented scheme over the other evaluated schemes.

In 2017, Chunhong et al. [16] have modeled varied image inpainting schemes which classified the corrupted images using a tight frame model. Also, the betterment of the presented scheme was analyzed over other schemes in terms of improved quality. In 2019, Hu et al. [17] have developed a novel non-reference quality assessment scheme that solved the Thangka IIQA issues. Finally, a state-of-the-art index was generated by the

adopted technique for IIQA that was associated with human vision. In 2019, Liu et al. [18] have dealt with the inverse issues of image inpainting model, for which multi-filters guided low-rank tensor coding was introduced. Besides, the presented scheme outperformed the traditional scheme concerning PSNR, and SSIM.

In 2019, Jiao et al. [19] have deployed the MLCN and encoder-decoder generator that have effectively restored the image. Moreover, the efficiency of the presented technique was illustrated via the simulation results. In 2019, Cheng and Li et al. [20] have developed a direction structure distribution analysis approach for MRF oriented inpainting schemes. Experimental outcomes have demonstrated that the proposed technique maintained better consistency with reduced cost on inpainting diverse types of corrupted images. In 2019, Tran and Hoang [21] have presented a novel digital inpainting technique, which considered the related data for restoring the intensities of pixels derived from the image dataset. Accordingly, for simulation purposes, 2D face images were assessed from public datasets.

In 2019, Anis et al. [22] have established method that considered the high-order PDE schemes for resolving the image inpainting and de-noising issues. Also, numerous arithmetical examples were provided that revealed the superiority of the presented model over the conventional methods. In 2019, Wali et al. [23] have developed the adaptive boosting method for TGV oriented image inpainting and denoising. Also, various investigational results have established that the presented model generates images with reduced artifacts. In 2018, Ding et al. [24] have adopted a novel exemplar-oriented image inpainting model that exploited the recently introduced scheme known as the PAMSE. Here, the adopted scheme proved the improved performance of the developed method in propagating texture and geometric structure in a simultaneous manner.

In 2018, Zhu et al. [25] have developed a new technique depending on CNN, which assisted in detecting the patch-oriented inpainting process. Finally, investigational outcomes demonstrated that the introduced scheme acquired better performance concerning running time, FPR, and TPR. In 2018, Karaca and Tunga [26] have offered a pattern and texture conserving interpolation-oriented approach for inpainting the lost regions in color images. Finally, the performance of the established scheme was evaluated on different color images with varied patterns and textures. In 2018, Yan et al. [27] have regarded the PSIS problem, and accordingly, a PSIS method was proposed depending on LC-based SIS. Finally, the analysis was carried out for computing the effectiveness of the developed model.

In 2018, Han et al. [28] have implemented a new "virtual view synthesis" scheme for a depth-image-oriented scheme that lessened the errors occurred during inpainting. At last, the investigational results have shown the superiority of the presented technique in achieving effective high-quality virtual view images. In 2018, Qin et al. [29] have established two approaches for reversible image recovery and visible-watermark elimination. Furthermore, the analysis outcomes have revealed the superiority and effectiveness of the presented scheme. In 2018, Lu et al. [30] have portrayed a novel MTC for restoring the images based on vectors. Further, experimentations on both real and synthetic images were carried out that proved the improved restoration performance of the developed approach.

In 2010, Xiong et al. [31] have established an efficient image compression scheme, which had combined the PAI for developing the visual redundancy in color images. Finally, the outcomes showed the betterment of the presented model in offering improved bit rate saving at better qualities. In 2018, Mariko et al. [32] have presented an image inpainting scheme that optimized the outline of the masked areas specified by users. The investigational outcomes have illustrated that the adopted technique performed higher results than traditional schemes without masked region restoration. In 2004, Criminisi et al. [33] have developed the approach for eliminating huge objects from digitalized images. Finally, investigational results have shown the enhancements made by the presented scheme.

In 2017, Li and Lv [34] have adopted a decoupled variational scheme for image inpainting in transform and image domain including Fourier and wavelet domain. The arithmetical experimentation and evaluations on diverse images have revealed the efficacy of the adopted scheme. In 2017, Wang et al. [35] have resolved the issues from the viewpoint of intensity function estimation. In the end, arithmetical experiments have confirmed the efficiency of the adopted technique, particularly in edge recovery. In 2017, Fuchs and Jan [36] have introduced an extensive analysis of higher-order issues that were simulated by numerical imaging applications. This work mainly concerned with higher-order bounded deviation along with dual solutions.

In 2019, Anh and Hoang [37] have established a new reconstruction approach that generated RGB images

without exploiting the descriptors. Finally, the experiments have shows the efficacy of the presented scheme. In 2016, Shen et al. [38] have developed a constrained inpainting scheme for recovering an image from its inaccurate or incomplete wavelet coefficients. From the analysis, the presented scheme recovered the images with better PSNR and visual quality over the existing methods. In 2016, Peter et al. [39] have established a novel approach which involves the comprehensive analysis of the weaknesses and strengths of the PDEs. Also, the analysis outcomes have offered simple harmonic diffusion and reduced compression rates when evaluated over the other existing schemes.

In 2017, Colomer et al. [40] have exploited the dictionary learning and sparse representation methods for inpainting the retinal vessels. Also, two diverse methods of evaluating the inpainting quality were offered that validated the non-artificial outcomes on inpainting. In 2015, Sarathi et al. [41] have presented approach for speedy automatic recognition of OD and its precise segmentation in digital eye images. Further, researches were performed on a labeled dataset with segmentation accuracy of 91%. In 2015, Zhang et al. [42] have presented an efficient and simple restoration approach based on image inpainting. The outcomes were found to have removed the noise efficiently while conserving the image details with improved PSNR.

In 2015, Li et al. [43] have established a fast local inpainting scheme depending on the "Allen–Cahn" approach. Also, numerous arithmetical outcomes were presented that portrayed the accuracy and robustness of the implemented scheme. In 2015, Jiao et al. [44] have presented a technique for restoring the highly corrupted digital "off-axis Fresnel holograms" depending on image inpainting. Besides, ABC was employed that increased the computational efficacy of the inpainting scheme. In 2015, Liang et al. [45] have introduced a forgery detection approach using exemplar-oriented inpainting. In the end, the simulation outcomes have illustrated the betterment of the presented scheme offers reduced processing time for varied images.

In 2014, Berntsson and George [46] have exploited the theory of parameter recognition as a method of inpainting. The arithmetical analysis and error analysis had shown the presented model's betterment over the harmonic inpainting model. In 2014, Margarita et al. [47] have deployed the preliminary image segmentation method, and accordingly, SOMs were created for every homogeneous texture. Further, the outcomes were compared over the traditional SOM schemes and the desired inpainting agents were portrayed. In 2014, Chung and Yim [48] have introduced an effective error concealment technique for reconstructing the pixels, which were lost during video communication. The developed technique also offered considerable enhancement on PSNR over the existing schemes.

In 2014, Li et al. [49] have modeled the exemplar-oriented inpainting approach for maintaining better neighborhood consistency and structural coherence. Also, the investigational results have revealed the improvements of the adopted scheme for diverse tasks like text removal, scratch removal, object removal, and block removal. In 2014, Chen et al. [50] have introduced edge detection scheme, which enhanced the conventional depth map inpainting approach using extracted edges. The implemented scheme had predicted the lost depth values effectively and it had proved an enhanced performance over the traditional algorithms. In 2016, Kawai et al. [51] have combined the local planes for enhancing the background geometry, and accordingly, the inpainting quality was enhanced. From the analysis, the modeled technique was found to be better over the other compared approaches.

In 2013, Zhao et al. [52] have presented a new passive recognition technique for inpainting the corrupted JPEG images when they were stored in JPEG compressed format. Finally, the investigational results have detected and located the lost region accurately with higher quality. In 2013, Qin et al. [53] have developed the self-recovery method for tampered images with image inpainting and VQ indexing. Moreover, the efficiency of the implemented approach was demonstrated from the experimental results. In 2013, Chang et al. [54] have modeled an innovative forgery detection scheme for identifying the corrupted inpainting images, which was considered as an effective scheme for image processing. In the end, experimental outcomes have illustrated that the introduced scheme was faster with excellent performance over the compared schemes.

In 2012, Dong et al. [55] have presented a blind inpainting method that identified and recovered the damaged pixels of the provided image. Finally, the experimentations have illustrated that the presented scheme was better over several two-staged approaches. In 2012, Zhang and Dai [56] have implemented a wavelet decomposition scheme for filling the corrupted image with both texture information and missing structures. Also, the adopted scheme restored the images quickly and the PSNR was also better under the conventional methods. In 2012, Liu

et al. [57] have established a patch-oriented image compressing model motivated by the inpainting approaches. The analysis outcomes have achieved a better gain and it has also saved the bit-rate at better quality. In 2011, Li et al. [58] have exploited the Chambolle's dual schemes that resolved the TV colorization scheme and TV inpainting scheme. From the numerical analysis, the presented scheme was found to be easier and faster for implementation.

In 2011, Du et al. [59] have developed model for image inpainting, for which MS method was exploited and also, the level set technique was deployed for estimating the structure of the corrupted portions. In 2010, Cai et al. [60] have developed integrated frame-oriented method for recovering the missing coefficients or bits throughout the process of compression. Finally, arithmetical experimentation had demonstrated the efficacy of the presented approach to enhance the visual quality of images. In 2010, Ojeda et al. [61] have developed an approach for carrying out image segmentation. Initially, an image was designed locally via an autoregressive approach. Furthermore, the investigational outcomes were offered that confirmed the practical efficiency of the presented algorithm.

In 2009, Li et al. [62] have adopted a restoration scheme, where the unwanted distortions get reduced in imaged documents. The efficiency of the introduced scheme was demonstrated through real and synthetic documents. In 2008, Cai et al. [63] have adopted iterative tight frame method for inpainting the images. Here, the relationship of the presented technique was discussed with other wavelet-oriented schemes, and its effectiveness was proved. In 2008, Wang and Sung [64] have introduced a new approach to automatic image recovery and authentication, where the distorted area of the image was recovered and detected automatically. At the final point, experimental outcomes were provided, which proved the efficacy of the presented approach. In 2007, Celia et al. [65] have adopted the method for restoring the images. The presented scheme also filled the corrupted or missing information along with noise removal.

3. A comprehensive review of adopted algorithms, Performance measures and the maximum achievements.

3.1. Analysis of Adopted Methods. This area makes a survey of various strategies embraced in each work, which is given in a diagrammatic depiction by Fig. 3.1. In the review, it was observed that Bregman method was exploited by [1, 13, 55] and Patch Scale Optimization was utilized in [3, 28, 33, 37, 57]. MRF scheme was adopted in [18, 20]. In addition, Wavelet transform model were adopted in [9, 12, 34, 56, 60, 63], while PDE schemes were adopted in [10, 14, 15, 22, 31, 39, 40, 46, 65]. Moreover, the TV-based model like the LRTV model was adopted in [5] and the TGV scheme was adopted in [23, 36, 38, 53]. Likewise, Gaussian approach was deployed in [4, 21, 24, 50], whereas NN based models like CNN was adopted in [19, 25, 42] and NN was used in [47]. FFT was adopted in [2, 7, 30]. Furthermore, Local gradient scheme, Criminisi algorithm, View synthesis method, Tight frame algorithm, Cross-correlation, LC model, Huffman coding, SVM, kernel Hilbert space, Region Growing model, Allen–Cahn model, ABC, Fragment splicing detection, Spatial interpolation, CGPS, Delaunay triangulation, forgery detection model, Chambolle's dual method, MS model, AR, RBF-smoothing and Wong's watermarking scheme were adopted by [35, 37-38, 41, 46, 48-49, 51, 56, 58-61, 63-64].

3.2. Analysis of Performance Measures. Table 3.1 depicts the performance measures determined in diverse contributions concerning image inpainting. From Table 3.1, it is noticed that PSNR performance analysis is done in 38 papers which contributed about 58.46% of the reviewed works, and 21 papers was analyzed on Computation time which contributed on 32.31% of the total works. Also, the SSIM, SNR, Standard deviation and MSE have been contributed around 16.92% (11 papers), 4.62% (3 papers), 4.62% (3 papers), and 9.23% (6 papers). Further, mean opinion score, error, and converging time have been adopted in 6.15% (4 papers), 7.69% (5 papers), and 4.62% (3 papers). Moreover, the Bit saving, GWN, AP, and compression have contributed about 3.08% of the entire contribution. Over 1.54% of total contributions have analyzed the measures like MSSIM, frequency of success, gain, no. of masked pixels, damage ratio, TPR, FPR, recall, maximum size, variance, subjective scores, versatility, sparsity, VSI, overlapping score, segmentation accuracy, CPU time, accuracy, computational speed missing ratio, frame rate, detection overlap, detection error, and tampering percentage respectively.
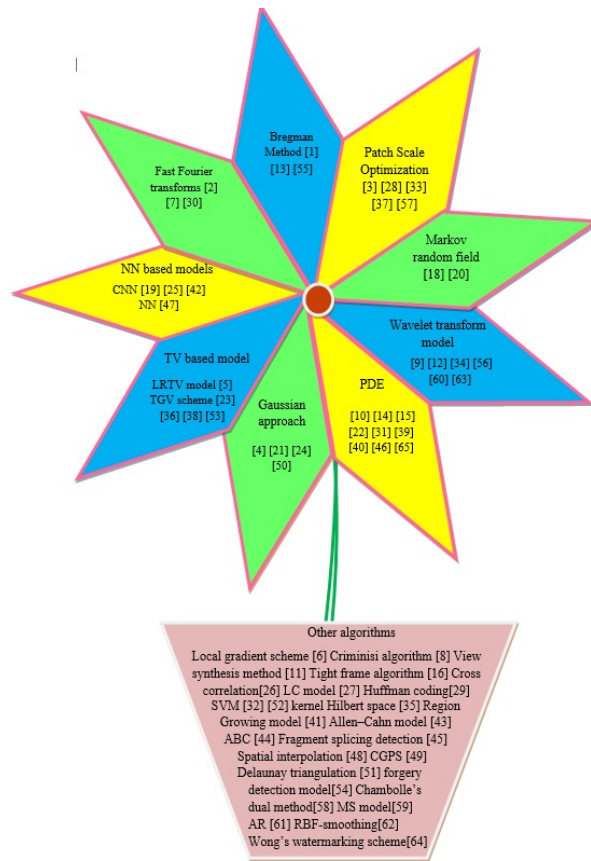
FIG. 3.1. *Pictorial Representation of the Adopted Methods for image in painting models in the reviewed works*

3.3. Maximum Performance. The most extreme presentation accomplished by all of the reviewed papers regarding the image inpainting system is shown in Table 3.2. In the review, PSNR presented in [29] has achieved a better value of 51.68dB, and computation time adopted in [6] has achieved a higher value of 0.44sec. Also, SSIM Value has achieved a better value of 0.8475 and it has been introduced by [19] and SNR Value has achieved a better value of 28.59 dB and it has been introduced by [16] respectively. Similarly, MSE, mean opinion score, error, and converging time have attained better values of 16.3269mm, 100, 0.043, and 1sec and it has been adopted by [4, 10, 17, 50]. The measures, bit saving, GWN, AP, compression and frame rate have attained higher values of 84.8%, 2%, 98.3, 7.751 and 29.94 fps and they have been adopted in [25, 29, 31, 35, 51]. Also, standard deviation, frequency of success, gain, number of masked pixels and damage ratio were introduced in [4, 6, 13-15], as well as they have obtained better values of 10, 1, 99.24%, 12469 and 7.5% correspondingly. Also, TPR, FPR, recall, Maximum Size, and Variance have attained higher values of 89.8, 1.4, 86.03%, 16 and 0.02 and they have been measured in [9, 10, 25, 54]. Also, tampering percentage, overlapping score, sparsity, segmentation accuracy, CPU time, accuracy and computational speed have attained higher values 33.9%, 0.91, 20%, 87%, 0.16s, 92% and 5,995ms correspondingly and they were presented in [34, 41, 43, 47, 53].

4. Assessment of adopted tools and chronological review in each work.

4.1. Review on Adopted Tools. The simulations of the reviewed works are made in diverse test systems such as MATLAB, C++, C, FreeFem++, Kakadu software, and so on. The pie chart representation of the adopted tools in the reviewed works is given by Fig. 4.1. In 29 papers MATLAB was implemented that have presented about 45% of the total contribution, and C++ was used in 4 papers which offered about 6% of the whole contribution. Also, the C language was offered in 1 paper and FreeFem++ have been presented in 1

TABLE 3.1
Review of various performance measures exploited for image inpainting schemes

Measures	Citations
PSNR	[2-6, 8-13, 16-22, 26-30, 34-35, 37-38, 42-43, 46, 48-49, 55-57, 60, 63-64]
Computation times	[2, 6-7, 14-15, 20, 23-24, 26, 30, 34, 40, 42, 44-45, 48-49, 51, 59, 62, 65]
SSIM value	[1, 3, 17-20, 22-23, 27-28, 37]
SNR value	[1, 16, 23]
MSE	[19, 21, 39, 48, 50, 61]
Mean opinion score	[17, 24, 40, 58]
Error	[2, 4, 43-44, 46]
Converging time	[10, 36, 38]
Bit saving	[31, 57]
GWN	[35, 61]
AP	[25, 54]
Compression	[29, 39]
MSSIM	[11]
Standard deviation	[13, 24, 58]
Frequency of success	[4]
Gain	[14]
No. of Masked pixels	[15]
Damage ratio	[6]
TPR	[25]
FPR	[25]
Recall	[54]
Maximum size	[9]
Variance	[10]
subjective scores	[32]
versatility	[33]
sparsity	[34]
VSI	[37]
Overlapping score	[41]
segmentation accuracy	[41]
CPU time	[43]
accuracy	[47]
computational speed	[47]
Missing ratio	[49]
Frame rate	[51]
Detection overlap	[52]
Detection error	[52]
Tampering percentage	[53]

paper, that has offered about 1% of the total contribution. Furthermore, Kakadu software has been exploited by 1 paper that contributes about 1% of the entire contribution. Accordingly, OpenCV library 2.3.1 was adopted by 2 papers that offer about 3.07% of the whole contribution.

4.2. Chronological Review. This review analyses various papers presented in different years. The percentage of contributions to corresponding years in pie chart format is illustrated in Fig. 4.2. Initially, 10.77% of papers are reviewed from the years, 2004-2009. Similarly, 18.46% and 21.54% of the total reviewed papers are existing in the year, 2010-2012 as well as 2013-2015. Moreover, 26.15% of contributions on image inpainting schemes are reviewed from the year 2016-2017. The papers reviewed for image inpainting in the years 2018-2019 is 23.07% of the whole contributions.

4.2.1. Research gaps and challenges. The research challenges and gaps on image inpainting systems are as follows:

- Image Inpainting [82, 83] is a technique that recovers the damaged images and it also concerns removing the undesirable portions from the image.
- This method eliminates the breaks in the image, eradicates the texts, and fills the missing part from the image.

TABLE 3.2
Review of various performance measures exploited for image inpainting schemes

| Sl. no	Author [Citation]	Performance measures	Maximum performance
1	[29]	PSNR	51.68dB
2	[6]	Computation Times	0.44sec
3	[19]	SSIM Value	0.8475
4	[16]	SNR Value	28.59 dB
5	[50]	MSE	16.3269mm
6	[17]	Mean opinion score	100
7	[4]	Error	0.043
8	[10]	Converging Time	1sec
9	[31]	Bit Saving	84.8%
10	[35]	GWN	2%
11	[25]	AP	98.3
12	[29]	Compression	7.751
13	[51]	Frame Rate	29.94 fps
14	[13]	Standard Deviation	10
15	[4]	Frequency of Success	1
16	[14]	Gain	99.24%,
17	[15]	No. of Masked Pixels	12469
18	[6]	Damage Ratio	7.5%
19	[25]	TPR	89.8
20	[25]	FPR	1.4
21	[54]	Recall	86.03%
22	[9]	Maximum Size	16
23	[10]	Variance	0.02
24	[53]	Tampering Percentage	33.9%
25	[41]	Overlapping Score	0.91
26	[34]	Sparsity	20%
27	[41]	Segmentation accuracy	87%
28	[43]	CPU time	0.16s
29	[47]	Accuracy	92%
30	[47]	Computational speed	5,995ms
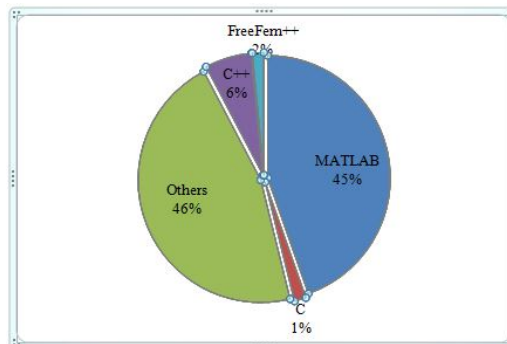
FIG. 4.1. *Analysis on adopted tools in reviewed works*

- Inpainting can be done by an individual, if he has more knowledge regarding this technique or if he is focused in that field [84, 85].
- However, owing to manual processes, it includes more time to offer essential results. For inpainting an ancient painting or to inpaint a scratched image with lost regions, it is required to estimate and fill up the missing image regions such that the painting or restored image appears as likely as its original version [86].
- Exactly, what formulates the inpainting issue so inspirational is the complexity of image benefits.
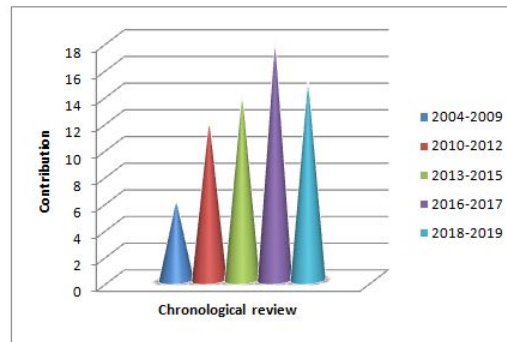- Also, the image functions with multilevel complexities have forced the analysts to develop inpainting

Fig. 4.2. *Bar chart representing a chronological review*

structures targeted at the real versions of images. Therefore, these inpainting approaches are at low stages.

- The significant challenging task in image inpainting method is the computation of the image quality, which should be the same before and after the inpainting process [87, 88].
- In recent days, various image inpainting schemes are available. Also, numerous attacks were deployed by the analysts for digital image inpainting that are categorized under the following classes such as, PDE based inpainting, hybrid inpainting, texture synthesis based inpainting, and exemplar-based inpainting. PDE oriented schemes can be well suitable for filling the little gaps, text overlay, and so on.
- However, the PDE method generally fails if exploited to the textured field or regions with regular patterns.
- The entire texture oriented schemes vary concerning their ability to produce texture with differed statistical features, gradient, and colour intensity.
- Also, the texture inpainting technique could not be adopted well for natural images and they do not include the capability to handle boundaries and edges effectively.
- At certain conditions, the user needs to decide which texture should be replaced by which one.

Thus, these schemes can be deployed for inpainting [89, 90] only the small regions, and more developments are required for inpainting the larger regions in an efficient manner.

5. Conclusion. This paper has introduced a survey of image inpainting models. In this, different methodologies adopted in the reviewed works were analyzed and exhibited. Moreover, this review analyzes the performance measures related with the reviewed image inpainting scheme. In conclusion,

▷ This paper looked around 65 research papers and stated a noteworthy investigation of different algorithms.

▷ The analysis has reviewed the performance measures and the corresponding maximum achievements contributed by different image inpainting schemes.

▷ Further, the various tools exploited in every reviewed works were also analyzed as well as specified diagrammatically.

▷ Also, the chronological review was done for the analyzed 65 works.

▷ Finally, this paper offered diverse research challenges that could be helpful for the specialists to accomplish more examination on the highlights of image inpainting schemes.

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