Rectification of Image Deformation using PSO-CNN approach

R. Kalyani [1], V. Vaitheeshwaran [2], U. V. Ramesh[3], CH. Bhavani[4], Ratnala prasad[5]

[1]Post/ Designation: Associate Professor Department: Department of Electronics and Communication Engineering Institute: Vidya Jyothi Institute of Engineering and Technology - Aziz Nagar Gate, C.B. Post, Hyderabad–500 075
Email: harebalu@gmail.com
[2]Associate Professor, Computer Science and Engineering Department, Aditya University, Surampalem, Kakinada Andhra Pradesh vaitheeshwaranv@adityauniversity.in
[3]Assistant Professor, Computer Science and Engineering Department, Aditya University, Surampalem, Kakinada Andhra Pradesh
veerarameshu@adityauniversity.in
[4]Associate Professor, Computer Science and Engineering Department, CVR College of Engineering, Hyderabad, Telengana, vbhavani118@gmail.com
[5]Assistant Professor, Department of Mechanical Engineering, Aditya University, Surampalem, Andhra Pradesh, prasadratnala2012@gmail.com

ABSTRACT

Tasks like document scanning, object recognition, and automated monitoring are greatly hindered by geometric distortion in images, which is often due to faulty camera angles, lens aberrations, or scene perspective. This paper, through combination of classic image processing techniques with metaheuristic and soft computing methodologies, presents an adaptive hybrid solution for distortion correction. Using Gaussian filtering and then Canny edge detection, images are preprocessed to highlight significant edges. Possible quadrilateral regions are identified by removing contours and using polygonal fitting to approximate them. These initial vertices are enhanced by the application of Particle Swarm Optimization (PSO). A fitness function based on geometric regularity, such aspect ratio and angle consistency, promises an optimum rectification mapping.

To reconstruct a geometrically rectified picture, the optimized corner points are then sent into the homography transformation.

With the purpose of increasing accuracy in scenarios like occlusion, shadowing, or poor illumination, a Convolutional Neural Network (CNN) is trained to predict the position of deformed picture vertices straight from raw pixel input. By incorporating learned spatial priors into the PSO's optimization, the CNN serves as a backup or fine-tuning technique for unpredictable detections. Experimental results signify that the proposed method outperforms traditional Hough or Radon-based correction algorithms in terms of pixel alignment, structural similarity, and correction precision, thus proving its robustness in a range of real-world circumstances. In applications including document analysis, remote sensing, and intelligent vision, this unified PSO-CNN system offers a scalable and training-efficient method for trustworthy geometric correction.

KEYWORDS: Gaussian filter, Canny edge, PSO, CNN, Image processing, Deformation

How to Cite: R. Kalyani, V. Vaitheeshwaran, U. V. Ramesh, CH. Bhavani, Ratnala prasad, (2025) Rectification of Image Deformation using PSO-CNN approach, Vascular and Endovascular Review, Vol.8, No.3, 75-85.

INTRODUCTION

Geometric distortion is a prominent problem in digital photography that occurs at the time of image capture, such as inclined camera, errors in lens, and external disturbances. These distortions could lead to tilted or twisted depictions of the information of interest including papers or signboards etc. when not nabbed directly [1-2]. Such distortions considerably subside the process such as picture registration, optical character recognition (OCR), and target recognition. Therefore, faithful and flexible methods for determining spatial distortions are crucial for enhancing picture quality and interpretation in a broad range of applications.

Conventional image rectification techniques such as the Hough and Radon transforms allow fundamental tilt correction, but cannot address geometric deformations, specifically in conditions with influenced warping, biased occlusion, or irregular illumination [3]. This shortcoming, draw attention to the necessity for hybrid tactics that include the most suitable features of both traditional and perspective methods. A multi-level image correction technique uses contour approximation and Canny-based edge detection to distinguish distorted quadrilateral areas. These detected vertices are consequently improved using Particle Swarm Optimization (PSO), which optimize the fitness function based on geometric regularity, such as preserving right angles and aspect ratios coherently with rectangular geometries.

In difficult background, when edge information is noisy or insufficient, a Convolutional Neural Network (CNN) is used to forecast the image vertices and its positions, precisely from image cues [4-5]. This predictive approach improves the optimization stage by providing accurate corner point predictions, particularly in low contrast environments.

Finally, the repaired vertices are used in a homography transformation to return the original picture to its original condition. The proposed PSO-CNN integrated approach ensures flexibility and resilience without requiring a lot of training data or demanding imaging conditions, enabling reliable restoration of damaged pictures under a range of real-world scenarios [6]. Several image correction methods have been proposed to rectify geometric distortions caused by camera angle, lens aberrations, or environmental conditions. Traditional methods such as the Hough Transform and Radon Transform have been widely used for tilt and skew correction by identifying projections or straight lines inside the picture [7]. Yu, Zhu, and Wang (2017) introduced a correction method for tracking pictures that combines the Radon transform with the Canny edge detection operator to effectively identify and fix damaged track features [8].

This technique increased the accuracy of image rectification by improving the detection of linear characteristics, even in noisy or low-quality pictures. This approach facilitates more precise track detection, which is beneficial for applications such as transportation monitoring and computer vision. Bafjaish et al. (2018) introduced a method for skew identification and correction using the Hough transform [9]. The technique successfully detects text line orientations and corrects skew, improving the readability and accuracy of digital processing of Quranic manuscripts.This work is significant for document recognition, preservation, and digitization systems. While these methods are effective for simple distortions, they often fail to repair complex non-linear geometric deformations because they are sensitive to edge clarity and noise. Although they have been studied as a way to get around these limitations and improve rectification through linear mapping, affine transformation techniques are still not very good at handling irregular quadrilateral transformations. More recently, machine learning and deep learning techniques have emerged as strong alternatives.

The accuracy of corner point prediction in natural environments was significantly improved by the proposal of a recursive CNN for real-time document localization [10]. This research proposes a novel recursive approach that uses a convolutional neural network (CNN) to locate documents in images of natural situations. Because the recursive CNN improves its predictions over time rather than studying the full image at once, it can accurately locate and crop document parts. This method is designed to be computationally efficient, enabling real-time document localization on consumer-grade hardware.The method can deal with issues like cluttered backdrops, uneven lighting, and perspective distortions since it uses a recursive process. The tests demonstrate that, in unrestricted settings, the approach performs better than conventional document detection methods. Yoo and Jun (2021) corrected skewed license plate photos using deep corner prediction models [4, 11]. Nevertheless, these models need a lot of labeled training data and frequently perform poorly in settings with a lot of background noise or occlusion. However, Deng et al. (2024) reduced the reliance on data and achieved greater resilience by proposing a spatial mapping-based homography technique for distortion correction of quadrilateral and triangular targets utilizing geometric vertex prediction and 3D space transformation [12].These advancements offer a solid basis for incorporating optimization methods such as CNNs with particle swarm optimization (PSO) can improve the accuracy of distortion correction in difficult imaging scenarios. Table 1 depicts the literature survey of the different image distortion correction methods.

Table: 1 Literature Survey

S. No.	TITLE	AUTHORS	YEAR OF PUBLICATION
1	Skew Detection and Correction of Mushaf Al-Quran Script Using Hough Transform	Bafjaish et al. [9]	2018
2	Correction Method of Track Image Based on Canny Operator and Radon Transform	Yu et al. [8]	2017
3	Methods for Digital Image Correlation Measurement with Camera Shake Correction	Li et al. [19]	2021
4	Real-Time Document Localization in Natural Images by Recursive Application of a CNN	Javed and Shafait [5]	2017
5	Deep Corner Prediction to Rectify Tilted License Plate Images	Yoo and Jun [4]	2021
6	An Algorithm of Deformation Image Correction Based on Spatial Mapping	Xiangyu Deng, Aijia Zhang, Jinhong Ye [1]	2024

METHODOLOGY

Despite being useful for tilt correction and line detection, Hough and Radon Transforms are only capable of handling basic distortions and frequently break down when an image has noise, low contrast, or a complicated background. Additionally, they necessitate precise thresholds and orientation-based assumptions.

Only a few forms of deformations, including rotation, scaling, and shearing, can be corrected by affine transformations. They are not enough to deal with non-parallel edges or perspective distortions in arbitrary quadrilaterals [13 -16]. CNN-based vertex prediction techniques, such those for license plate correction or document localization, need a lot of annotated data. The caliber and diversity of training data have a significant impact on their accuracy. Learning-based prediction and geometric optimization are not combined in the majority of current methods. This results in either a brittle detection based only on picture features or an over-reliance on training data.

The suggested framework for correcting image distortion is a hybrid model that combines deep learning, optimization methods, and conventional image processing.

1. Image preprocessing: To lower noise, the input image is grayscaled and then subjected to Gaussian blur. After highlighting object boundaries with Canny edge detection is used to extract contours. The Douglas-Peucker technique is used to approximate contours to polygons, and quadrilateral regions are chosen according to the number of vertices.
2. Vertex Detection and Approximation: An approximation is made of the identified quadrilateral's original corner points, or vertices. However, because to occlusion, shadows, or complicated backdrops, these points are frequently inaccurate in real-world situations [17].
3. Particle Swarm Optimization (PSO)-Based Optimization: PSO is used to hone these identified points. The corner points are repositioned to more closely resemble an ideal rectangle or shape thanks to a bespoke fitness function based on geometric features (such as side lengths, angle uniformity, and area symmetry). This improves the homography Transformation’s quality [18].
4. CNN-Based Vertex Prediction (Fallback/Enhancement): A trained Convolutional Neural Network (CNN) makes predictions about the vertex positions straight from the image when edges are noisy or absent. This guarantees resilience in real-time or low quality situations.
5. Homography and Warping: The deformed quadrilateral is mapped to a standard rectangular view by feeding the optimized or CNN-predicted corner points into a perspective transformation function (cv2.getPerspectiveTransform), which successfully corrects the geometric distortion [19].

PROPOSED SYSTEM

By combining deep learning, soft computing, and conventional image processing methods, the suggested system offers a reliable and flexible hybrid solution for correcting geometric distortion in pictures. The initial step in the proposed image processing procedure is grayscale conversion and Gaussian blur denoising of the input image. After highlighting salient edges with Canny edge detection, quadrilateral regions that are plausible candidates for distortion correction are identified using contour detection and polygon approximation. Following the extraction of the quadrilateral regions, the vertex positions are adjusted using Particle Swarm Optimization (PSO). In order to guarantee that the corners form a mathematically coherent rectangle maintaining equal opposite sides and right angles, PSO minimizes a specially created fitness function. This phase makes the system adaptive to uneven or skewed geometry.

Convolutional Neural Network (CNN) is used to forecast the vertex coordinates straight from the raw image when the edge information is uncertain, missing, or deteriorated. The system can retain great accuracy under a range of imaging situations because to this dual-track technique [20]. In order to properly correct geometric deformations, a homography transformation is performed using the optimized or predicted vertices. The deformed area is mapped to a parallel to the front, normalized picture using this transformation.

By combining edge detection with CNN-based vertex prediction, this suggested system may function well in scenarios where traditional methods are inefficient, such as low light levels, noisy surroundings, or partial occlusion, confirming resilience to noise and occlusion.

PSO improves the precision of the homography correction beyond what can be accomplished with simple contour detection by ensuring that the detected quadrilateral or region closely resembles the ideal geometry achieving the optimized driven accuracy. The technology is applicable to a wide range of use cases, including remote sensing photos with deformed land parcels or features, document scanning, license plate correction, and traffic sign rectification.

INTRODUCTION TO IMAGE DISTORTION CORRECTION USING EDGE DETECTION, PSO OPTIMIZATION, AND CNN-BASED VERTEX PREDICTION

Image Preprocessing

A key component of the suggested distortion correction methodology is image preprocessing. To cut down on computing complexity and concentrate on intensity changes rather than color fluctuations, the original input image typically in RGB color space—is first transformed to a grayscale image. This stage highlights image structures and streamlines the data.

The image is subjected to Gaussian blur after grayscale conversion in order to reduce high-frequency noise that could obstruct edge recognition. By utilizing a Gaussian kernel to average pixel intensities with their neighbors, the Gaussian filter smoothen the image. This is especially helpful for minimizing small illumination irregularities or salt-and-pepper noise.

The Canny edge detection algorithm is used once the noise has been minimized. Hysteresis thresholding, non-maximum suppression, and gradient computation are all steps in the multi-stage process of canny edge detection. As a result, the strong input edges are highlighted in the binary image. These edges, which are essential for later contour

Identification, are usually the borders of objects. Next, the binary edge map's contours are taken out using Open CV's find Contours method [21]. Every contour is a curve that connects every continuous point along the same intensity boundary. The resulting contours may depict intricate or chaotic shapes and are frequently asymmetrical. Consequently, the Douglas-Peucker algorithm is used to approximate the contours to polygons.

The shape is made simpler in this step while maintaining its overall structure. These polygons are filtered out of forms that are too small or unimportant by selecting quadrilateral regions based on the number of vertices and contour area.

Finding the vertices or corner points of the quadrilateral regions that have been chosen is the next stage. The first approximations for the correction procedure are the vertices. However, these detected points are frequently erroneous or lacking because of flaws in real-world situations, like dim lighting, occlusion by other objects, or motion blur.

The identified vertices need to be rearranged and verified in order to increase accuracy. This entails arranging the vertices according to their spatial coordinates in a consistent order (top-left, top-right, bottom-right, and bottom-left). Reliable perspective transformation later on depends on this sorting. Inaccuracies like skewed angles or uneven side lengths can still exist even with sorted points [22]. As a result, the main goals of this step are to clean up the detection output, extrapolate any missing points, and get the data ready for optimization. In practice, this could entail removing convex shapes, validating shapes using anticipated aspect ratios or angles, and utilizing geometric heuristics to infer accurate point placements.

For high-precision picture correction, the initial vertex detection stage frequently yields approximations, which may not be optimal. Particle Swarm Optimization (PSO), an optimization method inspired by nature, to improve these findings. PSO iteratively updates the placements of particles (candidate solutions) based on personal and global best solutions, simulating the movement of fish schools or bird flocks towards the ideal solution.

Each particle in this system is a possible arrangement of the distorted quadrilateral's four corner points. Finding the ideal arrangement that most closely resembles a real rectangle is the aim. The configuration of each particle is assessed using a specially designed fitness function.

- Angle Uniformity: Penalizes interior angles that deviate from 90 degrees.
- Consistency in side length: Guarantees that opposing sides are comparable length.
- Consistency of area: Maintains the area within a predetermined range.
- Symmetry: Encourages vertices to be geometrically balanced.

To reduce the fitness value, PSO modifies the particle placements throughout a number of iterations. This gives a finely tuned set of corner points that nearly match the geometry of a typical rectangle. The correctness and dependability of the ensuing homography transformation are significantly increased by this modification.

LIST OF MODULES:

- Image Preprocessing
- Vertex Detection and Approximation
- PSO – based Optimization
- CNN based vertex prediction
- Homography and Warping
-

Image Preprocessing

Digital image processing (DIP) is the process of processing images digitally on a computer. Despite the primary emphasis on images, this field is essentially a subset of systems and signals. The main goal of DIP is to build a computer system that can process images. A digital image is fed into the system, which then applies a sophisticated algorithm to it. As a result, problems like noise and distortion accumulation may be avoided and a wider range of
algorithms may be utilized to evaluate the incoming data.

- Bringing the picture in by use of image capture software
- Image analysis and tweaking
- Picture editing

The preprocessing refers to operations carried out on images at the most basic level of abstraction. Both the input and the output are images of intensity. In the image-editing workflow, pre-processing is the stage where certain, important components are optimized to provide cleaner results in later stages.

A crucial first step in any computer vision pipeline is image preprocessing, particularly for applications involving geometry rectification. This stage's primary goal is to improve the image by highlighting significant structures like
Edges and boundaries and minimizing extraneous details and noise [23-24].

1. Conversion from Gray scale:

To simplify, the original image, which is usually in RGB format, is transformed to grayscale. By reducing the three-channel image to a single channel, this transformation preserves structural information while making future procedures simpler.

2. Gaussian Blur:

Gaussian blur is applied to images to minimize noise and detail. The procedure convolves the image with a Gaussian kernel G(x,y).

3. Perceptive Edge Recognition:

Strong edges are highlighted using the Canny edge detector. Double thresholding, non-maximum suppression, and gradient computation are all included.

4. Recognizing contours used to extract contours from the edge map. A curve that connects all the continuous points with the same intensity is called a contour. Usually, these contours are either closed or open arcs that encircle areas of interest.
5. Approximation of Polygons:

Using the Douglas-Peucker technique, contours are roughly converted into more straightforward polygonal shapes. The procedure recursively eliminates points from a given contour until it produces a shape with fewer vertices, such as a quadrilateral.

6. Selection via Quadrilaterals:

Filtering polygons with precisely four vertices and an adequate area allows quadrilaterals to be chosen from among all identified shapes. Only significant areas—such as documents, signboards, and plates—are advanced to the following phase thanks to this step.

Vertex detection and approximation

Finding a quadrilateral region's corner points (vertices) is a crucial next step after a quadrilateral region has been successfully identified using the contour detection and polygon approximation method. Since these points define the geometric boundary required for perspective modification, accurate vertex recognition is crucial. However, the originally identified corners might not precisely match the actual geometry of the item because of flaws in real-world

Situations such as illumination, shadows, folds, occlusion or motion blur.

a. First Vertex Identification: The four vertices of a detected quadrilateral are usually provided by the polygon approximation phase. These points, though, might be arranged incorrectly and without order. The vertices must be sorted in the following sequence for homography to produce consistent results: top-left, top-right, bottom-right, and bottom-left.

b. Vertex Sorting: Their (x, y) coordinates are typically used for sorting.

- The least sum (x + y) is found at the upper-left point.
- The sum is highest at the bottom-right.
- The smallest difference (x-y) is found at the upper-right spot.

PSO-based Optimization

Although quadrilateral shapes' estimated vertices can be found using conventional contour and polygon approximation techniques, these methods frequently fail in practical situations. Inaccurate corner detection can be caused by noise, occlusion, distorted angles, and shadows. Particle Swarm Optimization (PSO) is used to improve the vertex placements in order to overcome these drawbacks. PSO is a bio-inspired optimization algorithm that takes inspiration from fish and bird social behavior. A proposed solution, in this example a collection of four vertex coordinates, is represented by each "particle" in the swarm. In order to minimize an objective function (also known as a fitness function), which measures how "rectangular" the detected shape is, these particles scan the search space.

$$v_i(t+1) = \omega\, v_i(t) + c_1\, (P_i(t) - x_i(t) + c_2\, (G(t) - x_i(t)$$
$$x_i(t+1) = x_i(t) + v_i(t+1)$$

$\omega\, v_i(t)$ is interia,c_1, c_2 are acceleration coefficients, the cognitive component as '$c_1\, (P_i(t) - x_i(t)$' and the social component as '$c_2\, (G(t) - x_i(t)$'. Thus new position and velocity vector translates the position to new position in the search space. The degree to which a quadrilateral approximates a rectangle should be reflected in the PSO's unique fitness function. Typical fitness functions consist of:

- Angle Deviation: Reduce each vertex departure from 90 degrees.
- Consistency in opposite side length: Opposite sides have to be almost equal

CNN-Based Vertex Prediction (Fallback/Enhancement)

The precision of the initial contour detection determines how successfully PSO optimizes initially discovered vertices. Contour-based techniques might not work if the edges are too noisy, deformed, or partially absent because of folds, occlusions, or shadows. We use Convolutional Neural Networks (CNNs) as a backup mechanism based on deep learning to address this. A dataset of photos with tagged corner points is used to train the CNN model. It gains the ability to directly forecast the locations of the four vertices and extract spatial characteristics from the image. This method offers resilience in demanding settings and does away with the need for edge quality.

The coordinates of the four corners are provided by the regression output, which is the result of the CNN architecture's numerous convolutional layers, pooling layers, and fully connected layers. After training, the model makes real-time predictions about the locations of its vertices on unseen images. This CNN-based vertex prediction serves as a backup or supplementary method. The convergence and stability of the optimization can be improved in reality by combining the CNN output with PSO and using the predicted points as the initial particle placements in the swarm.

Homography and Warping

After obtaining the final vertex coordinates the CNN, PSO correct the distortion using a homography transformation. A perspective change known as "homography" converts a quadrilateral area in the source image to a rectangle in the final image. A 3x3 transformation matrix that specifies the mapping between the source points are detected and the target points (standard rectangle corners) is calculated using transform function. The corrected image is then produced by applying the transformation using this matrix and warp perspective. This process effectively removes the distortion, curved edges are straightened, and normalizes the object's geometry.

Following correction, the picture can be utilized for further purposes such as measuring, object categorization, or optical character recognition (OCR).

Here, La indicates the variance of the side length tilted angle and Ia represents the variance of the interior angle for the quadrilateral and T represents the running time. The slope of the left, top, right and bottom sides of the corrected is indicated by $x_a, x_b, x_c and\ x_d$ of quadrilateral image. $x_1, x_2, x_3\ and\ x_4$ represents the slope of the four sides of the rectangle, which are 90°, 0°, 90° and 0°.

$$L_a = \frac{(x_a - x_1)^2 + (x_b - x_2)^2 + (x_c - x_3)^2 + (x_d - x_4)^2}{4}$$

$$I_a = \frac{1}{n}\sum_{i=1}^{n=4}(x_i - x)^2$$

RESULTS

The experiments were conducted on a system equipped with an Intel Core i7 with 16 GB RAM. A dedicated GPU was utilized to accelerate deep learning computations and optimization processes. These hardware specifications ensured efficient execution of CNN-based feature extraction and PSO optimization, as well as real-time performance evaluation of the image correction pipeline.

Coordinate System:

To assist in measuring distortions, skew, and angle changes, a reference coordinate system is shown alongside the input image. This indicates the degree to which the image deviates from the optimal rectangular alignment and serves as the baseline for correction.

Fig 2. a) Input image b) Grayscale and Blurred c) Canny Edges

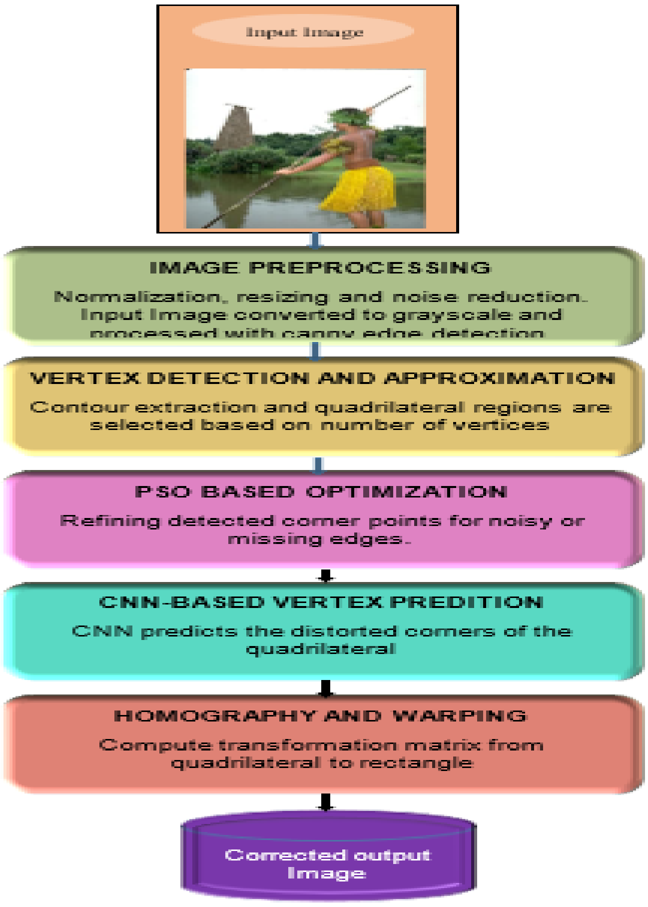

Fig 1. Implementation Methodology Flowchart

The unprocessed, raw input picture that has distortions such perspective faults or skew. The original picture is transformed into an intensity-based grayscale format figures [2-7]. This reduces computing complexity by eliminating color information and retaining just structural data that are necessary for additional processing. The Gaussian blur (or a comparable filter) is used to smooth the grayscale picture. Blurring increases edge detection by lowering noise and extraneous features. The borders of the object or document are highlighted using Canny edge detection. Creates the crisp outlines required to identify skew angles, corners, and lines. Measured in relation to the horizontal axis are the angles of the identified quadrilateral/document sides. Aids in measuring the image's tilt and distortion. The quadrilateral's interior angles are calculated. In a completely rectangular paper, they should ideally be 90 degrees apart. Non-parallelism or skewness of the identified object is indicated by variation in the side angles. Less variation indicates a closer correction, whereas high volatility indicates greater distortion. Calculates the deviation of the internal angles from 90°. A decreased variance means that the quadrilateral is nearer to a perfect rectangle after adjustment. Shows how long the detection and correction process takes in its whole. Used to assess the suggested method's effectiveness.

Fig 3. Contours detected for BerkleyTest image

To mimic skew, a manually slanted replica of the original image is compared with it.This illustrates how the system responds to distortions that are imposed purposefully. Quadrilateral corners are fine-tuned using Particle Swarm Optimization (PSO). By successfully aligning into a rectangular form, the resulting corrected picture lowers variance and skew.
Side Angles (deg): [1.91   91.97 -177.95 -91.97]
Interior Angles (deg): [93.88 90.07 90.07 85.98]
La (angle variance): 10210.5645
Ia (interior angle variance): 7.8146
T (runtime in seconds): 0.0017

Fig 4. Tilted and Corrected of BerkleyTest image

Angle Measurement Outputs
Following sorting and contour approximation, the system calculates angles to verify the geometric accuracy:

Raw variance before to optimization is indicated by La (Line Angle Variance): 10210.5645.
The interior angle variance, or Ia, is 7.8146, which indicates a slight departure from rectangular geometry.
These findings aid in measuring the degree to which the shape resembles a real rectangle both before and after optimization.

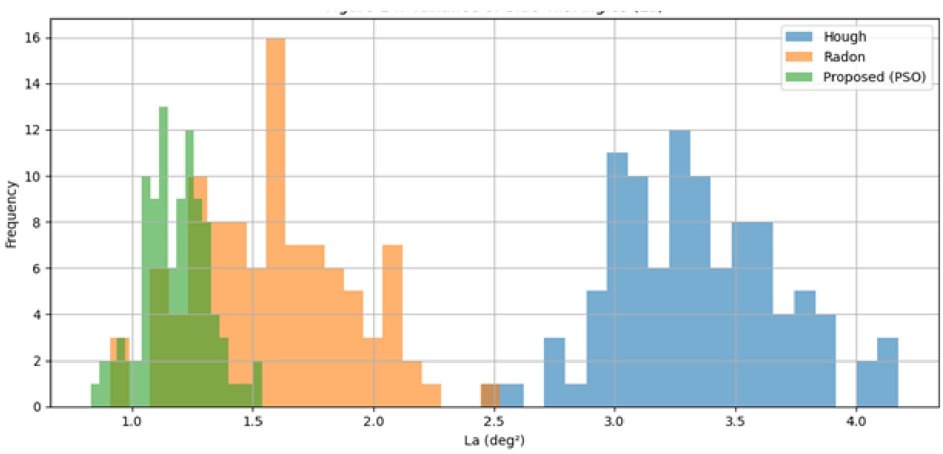

Fig 5. Variance of side Tilt angle La

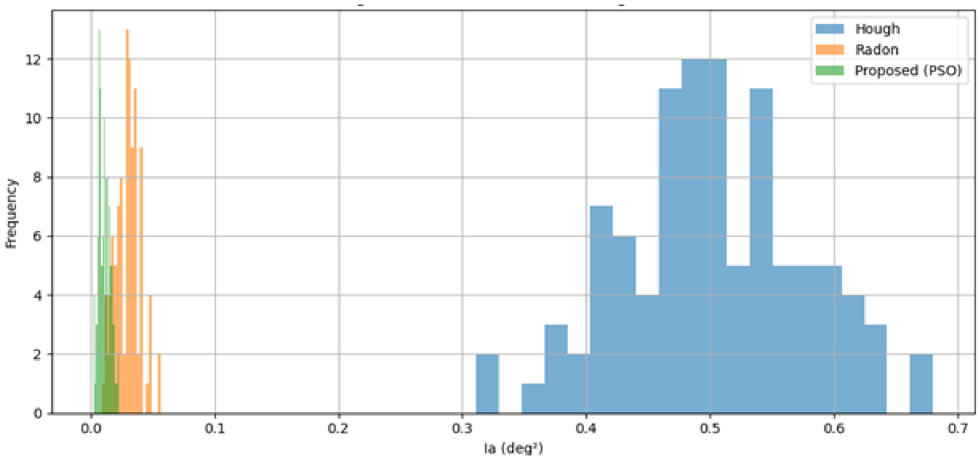

Fig 6. Variance of side Tilt angle Ia

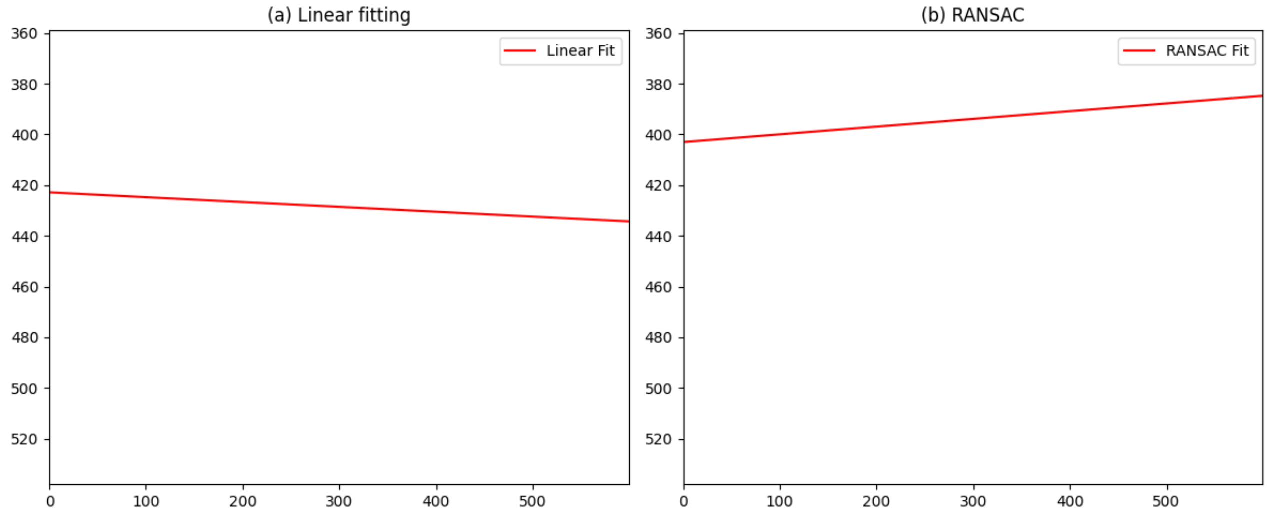

Fig 7. Execution time distribution of Linear and RANSAC Fitting

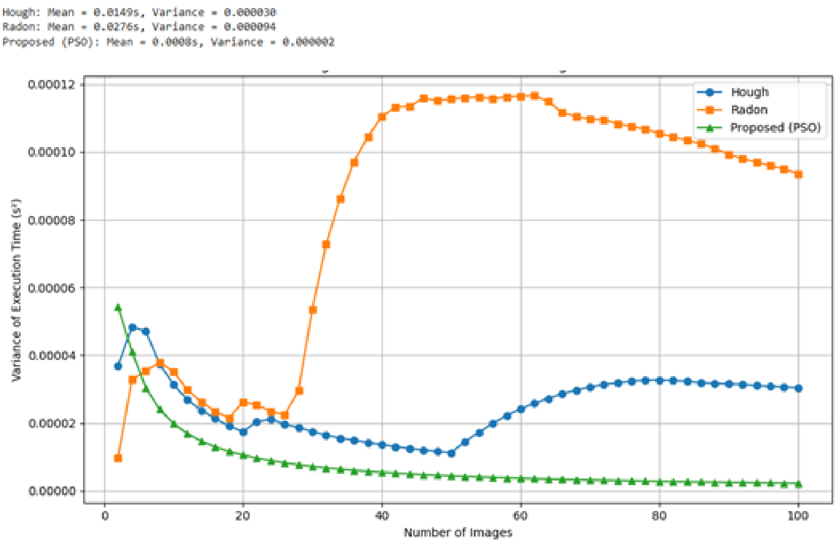

Fig 8. Mean and Variance of Hough, Radon and Proposed PSO

Performance Curve: Mean versus Variance

A comparative figure showing Mean Angle Accuracy vs. Angle Variance was made for each method in figure [8]. PSO had the lowest variance and the highest mean alignment.

The results of the manual and linear techniques were inconsistent; Hough and Radon showed moderate to high variation.

CONCLUSIONS AND FUTURE SCOPE

A hybrid method for repairing geometric distortions in photographs is presented in this paper, with a focus on quadrilateral areas such as documents, boards, or signboards. In order to extract structural boundaries, the pipeline starts with preprocessing using grayscale conversion, Gaussian blurring, and Canny edge detection. Following the refinement of quadrilateral candidates, detected contours are roughly converted to polygons.

Particle Swarm Optimization (PSO) is used to optimize vertex placements based on geometric attributes such side length similarity and angle uniformity in order to increase accuracy beyond traditional detection. Efficacy is ensured by using a fallback Convolutional Neural Network (CNN) to forecast vertex positions in case with noise, blockage, or low illumination. Conclusively, a homography transformation is used at the discriminating points to yield a result that is corrected and accurate.
Future Scope:

1. Real-time Application: To facilitate real-time video frame correction, the method can be additionally enhanced with GPU acceleration. This makes it suitable for AR/VR, mobile scanning, and drone based imaging.
2. Multi-Page Document Correction: Document digitization platforms can benefit from extending the system to include several quadrilaterals in one frame.
3. Powerful CNN Induction: The CNN can execute better under complicated situations such as textured backgrounds, tilted angles, and low illumination levels on various datasets.

Conflicts of Interest: The authors declare no conflict of interest.
Funding Declaration: This research received no external funding.

Data Availability:
This research paper utilizes ‘Berkley Standard Test Images’ data from the link mentioned www2.eecs.berkeley.edu/Research/Projects/CS/vision/bsds/BSDS300/html/dataset/images.html which is openly available.

Competing Interest declaration: I declare that I have no competing interests.

REFERENCES

1. X. Deng, A. Zhang, and J. Ye, “An Algorithm of Deformation Image Correction Based on Spatial Mapping,” *Chinese Journal of Electronics*, vol. 33, no. 5, pp. 1326–1336, 2024. DOI: 10.23919/cje.2022.00.443.
2. B. Fu, H. Guo, X. L. Zhao, et al., “Motion-blurred SIFT invariants based on sampling in image deformation space and univariate search,” *IET Computer Vision*, vol. 10, no. 7, pp. 709–717, 2016.
3. Z. L. Su, L. Lu, F. J. Yang, et al., “Geometry constrained correlation adjustment for stereo reconstruction in 3D optical deformation measurements,” *Optics Express*, vol. 28, no. 8, pp. 12219–12232, 2020.
4. H. Yoo and K. Jun, “Deep corner prediction to rectify tilted license plate images,” *Multimedia Systems*, vol. 27, no. 4, pp. 779–786, 2021.
5. K. Javed and F. Shafait, “Real-time document localization in natural images by recursive application of a CNN,” in *Proc. 2017 14th IAPR Int. Conf. Document Analysis and Recognition (ICDAR)*, pp. 105–110, Nov. 2017. DOI: 10.1109/ICDAR.2017.26.
6. M. Lee, H. Kim, and J. Paik, “Correction of barrel distortion in fisheye lens images using image-based estimation of distortion parameters,” *IEEE Access*, vol. 7, pp. 45723–45733, 2019.
7. R. A. Rakow-Penner, N. S. White, D. J. A. Margolis, et al., “Prostate diffusion imaging with distortion correction,” *Magnetic Resonance Imaging*, vol. 33, no. 9, pp. 1178–1181, 2015.
8. M. Y. Yu, Q. G. Zhu, and Y. J. Wang, “Correction method of track image based on Canny operator and Radon transform,” *Journal of Computer Applications*, vol. 37, no. S2, pp. 91–94, 133, 2017.
9. S. S. Bafjaish, M. S. Azmi, M. N. Al-Mhiqani, et al., “Skew detection and correction of Mushaf Al-Quran script using Hough transform,” *International Journal of Advanced Computer Science and Applications*, vol. 9, no. 8, pp. 402–409, 2018.
10. J. Kennedy and R. Eberhart, “Particle swarm optimization,” in *Proc. IEEE Int. Conf. Neural Networks*, Perth, WA, Australia, vol. 4, pp. 1942–1948, 1995.
11. S. W. Zhang, X. N. Zhang, Z. Y. Wu, et al., “Research on asphalt mixture injury digital image based on enhancement and segmentation processing technology,” *Applied Mechanics and Materials*, vol. 470, pp. 832–837, 2013.
12. M. M. Mohammed, A. Badr, and M. B. Abdelhalim, “Image classification and retrieval using optimized pulse-coupled neural network,” *Expert Systems with Applications*, vol. 42, no. 11, pp. 4927–4936, 2015.
13. Y. C. Chen, F. Y. Huang, B. Q. Liu, et al., “Significant obstacle location with ultra-wide FOV LWIR stereo vision system,” *Optics and Lasers in Engineering*, vol. 129, article no. 106076, 2020.
14. S. Zhang, B. Q. Liu, F. Y. Huang, et al., “Super wide field of view staring infrared imaging technology and its application,” *Laser & Infrared*, vol. 46, no. 10, pp. 1176–1182, 2016.
15. K. Koolstra, T. O’Reilly, P. Börnert, et al., “Image distortion correction for MRI in low field permanent magnet systems with strong B0 inhomogeneity and gradient field nonlinearities,” *Magnetic Resonance Materials in Physics, Biology and Medicine*, vol. 34, no. 4, pp. 631–642, 2021.
16. X. Huang, X. Zhang, and Y. Wang, “Document image dewarping using text line detection and CNN regression,” in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Seattle, WA, USA, 2020.
17. D. M. Feng, M. Q. Feng, E. Ozer, et al., “A vision-based sensor for noncontact structural displacement measurement,” *Sensors*, vol. 15, no. 7, pp. 16557–16575, 2015.
18. B. Y. Liu, L. D. Wu, H. X. Hao, et al., “Interferometric phase image denoising method via residual learning,” *Journal of Electronic Imaging*, vol. 30, no. 2, article no. 023013, 2021.
19. L. L. Li and H. B. Ma, “Pulse coupled neural network-based multimodal medical image fusion via guided filtering and WSEML in NSCT domain,” *Entropy*, vol. 23, no. 5, article no. 591, 2021.

20. Y. Mo, X. D. Kang, P. H. Duan, et al., “Attribute filter based infrared and visible image fusion,” *Information Fusion*, vol. 75, pp. 41–54, 2021.
21. B. Meher, S. Agrawal, R. Panda, et al., “A survey on region based image fusion methods,” *Information Fusion*, vol. 48, pp. 119–132, 2019.
22. X. H. Yang, Y. Xu, Y. H. Quan, et al., “Image denoising via sequential ensemble learning,” *IEEE Transactions on Image Processing*, vol. 29, pp. 5038–5049, 2020.
23. L. Ma, “Research on distance education image correction based on digital image processing technology,” *EURASIP Journal on Image and Video Processing*, vol. 2019, no. 1, article no. 18, 2019.
24. M. Alipour, S. J. Washlesky, and D. K. Harris, “Field deployment and laboratory evaluation of 2D digital image correlation for deflection sensing in complex environments,” *Journal of Bridge Engineering*, vol. 24, no. 4, article no. 04019010, 2019.