STUDY AND ANALYSIS OF IMAGE DECOLORIZATION TECHNIQUES

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in
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CANDIDATE'S DECLARATION

I, **Kurva Rajender (23/SPD/05)**, hereby certify that the work which is being presented in the major project report II entitled "**Study and analysis of Image Decolorization techniques**" in partial fulfilment of the requirements for the award of the Degree of Master of Technology, submitted in the **Department of Electronics and communication Engineering**, Delhi Technological University is an authentic record of my own work carried out during the period from August 2023 to April 2025 under the supervision of **Dr. N. Jayanthi.**

The matter presented in the thesis has not been submitted by me for the award of any other degree of this or any other Institute.

Candidate's Signature

This is to certify that the student has incorporated all the corrections suggested by the examiners in the thesis and the statement made by the candidate is correct to the best of our knowledge.

N. Jay 30/5/25

Signature of Supervisor (s)

Signature of External Examiner

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CERTIFICATE BY THE SUPERVISOR

I hereby certify that the Project titled "**Study and Analysis of image decolorization techniques**", submitted by **Kurva Rajender**, Roll No. 23/SPD/05, Department of Electronics and Communication Engineering, Delhi Technological University, Delhi in partial fulfillment of the requirement for the award of the degree of **Master of Technology** (M.Tech) in Signal Processing & Digital Design is a genuine record of the project work carried out by the student under my supervision. To the best of my knowledge this work has not been submitted in part or full for any Degree to this University or elsewhere.

N.Jay 30/5/25

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Date:30/05/2025 — Associate Professor

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ABSTRACT

Color information is often redundant when it comes to recognizing critical edges and features in a wide range of use cases. In image processing, converting a color image to grayscale helps eliminate redundant or non-essential color information. The current proposal is a novel approach for transforming a RGB image into Grayscale image based on Fusion of ICA and PCA. ICA is applied on color image to find independent components to make unique structures clear and the ICA output is 3 components per pixel. Applying PCA on the ICA output to find linear combination (principal component) which captures maximum overall variation and selecting first Principal component (PC1) which is most information rich and normalizing the PCA output. For Better contrast and clarity at the local level, the resultant grayscale image is processed with Contrast Limited Adaptive Histogram Equalization. This approach yields a grayscale image that better reflects the image's intrinsic intensity distribution while preserving more perceptual color information than traditional methods. Qualitative analysis has been done, and it shows that proposed method outperforms existing state-of-art techniques.

Key words: Decolorization, Grayscale image, PCA, ICA

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List of Abbreviations

PIQE - Psychovisually -based-Image-Quality-Evaluator

NIQE- Natural Image Quality Evaluator

CLAHE- Contrast Limited Adaptive Histogram Equalization

PCA- Principal component Analysis

ICA-Independent component Analysis

CHAPTER 1
INTRODUCTION

1.1 Overview

The conversion of color images to grayscale images is essential for various common place applications in computer vision and image processing [1]. A benefit of translation is that it provides the application of single-channel algorithms to color images, e.g. The Canny operator is employed for edge detection. Supplementary applications are monochrome printing, image recognition, others [29]. All these factors have facilitated the development of several color images to gray scale image conversion techniques previously. The process of translating color images to gray images involves mapping a three-dimensional vector to a one-dimensional scalar, constituting a dimensionality-reduction method that inevitably results in some information loss. Consequently, various sophisticated algorithms have been developed to effectively utilize the restricted range of gray scales for displaying the details and contrasts of input color images.

In a lot of computer vision and machine learning tasks, color images are routinely turned into grayscale images before they are processed. This makes the processing easier and faster. Three channels make up most color images: Red, Green, and Blue (RGB). Each channel adds to the overall pixel intensity. Processing all three channels at the same time uses more memory and processing power, which is especially true for large datasets or systems that need to work in real time. Making the images grayscale reduces the data amount your computer must process. Consequently, models used for edge identification, shape recognition and texture analysis perform faster and are less likely to overfit [1].

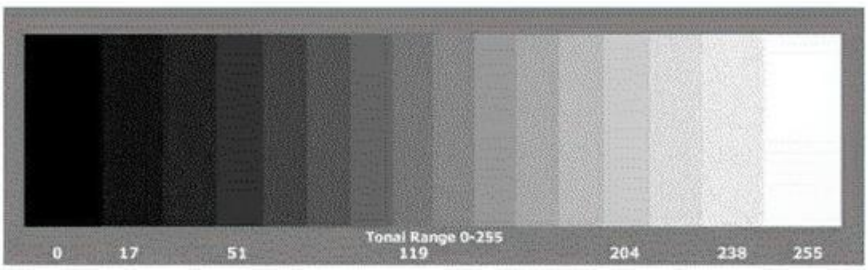

Fig 1.1: Sample of the Gray Scale Image.

1.2 Problem Statement

Conventional methods for removing color either they remove too much data or require time and resource-consuming ways to optimize. When tested using no-reference picture quality methods including NIQE and PIQE, different current techniques provide mixed results with varying image material [23]. As a result, the main challenge is to find a way to decolor images that is steady, efficient and produces visually accurate images in gray for a variety of datasets.

1.3 Motivation

More and more experts suggest that techniques such as PCA and ICA help with representing and transforming images. With orthogonal transformations, PCA seeks out the highest amount of data variance, whereas ICA tries to separate statistical-independent signals from within the mixed image channels, frequently bringing out features that are not Gaussian.

Our proposed methodology leverages the fusion of ICA and PCA, hypothesizing that ICA can extract underlying independent features from RGB channels, and PCA can prioritize and fuse them optimally for decolorization. This dual-stage statistical fusion model offers a novel pathway for image decolorization, targeting enhanced perceptual fidelity. Further, enhancement techniques such as **CLAHE (Contrast Limited Adaptive Histogram Equalization)** are integrated to improve the local contrast and fine details, particularly in low-contrast regions.

1.4 Objectives

The primary objective of this thesis is to critically analyse state-of-the-art image decolorization methods, identify their limitations in perceptual fidelity and computational efficiency, and develop an enhanced algorithm that addresses these gaps. Specifically, this work aims to:

1.4.1 Compare and Contrast Existing Methods:

Systematically evaluate global mapping (Gooch, Grundland & Dodgson), local contrast preservation (Lu), and learning-based approaches (Wu) to highlight their strengths and weaknesses in handling iso-luminant regions, computational overhead, and artifact generation. For instance, while Grundland's linear fusion achieves real-time performance, it fails to preserve fine details in low-contrast scenes.

1.4.2 Develop an Enhanced Decolorization Algorithm

Propose a hybrid frame work integrating independent component analysis and principal component analysis. Leveraging the benefits of two methods to balance perceptual accuracy and efficiency.

1.5 Applications and Significance

The proposed method finds significant applications in:

- **Medical Imaging**: Where accurate grayscale conversion preserves diagnostic details.
- **Artistic Rendering and Photography**: Where mood and texture preservation are essential.
- **Accessibility Tools**: For color-impaired individuals, a faithful grayscale image enables effective scene understanding.
- **Preprocessing in Vision Tasks**: Improved grayscale inputs benefit object detection, edge detection, and image segmentation.

This thesis contributes an innovative, computationally light, and performance-stable method to the literature of perceptually optimized image decolorization.

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CHAPTER 2
RELATED WORK

2.1 Literature Survey

To properly integrate the discriminant chrominance and contrast information from grayscale photos, akin to that in original color images, numerous approaches have been devised. Among the prevalent image decolorization processes, the typical or most widely used are the method employed by National Television Standard Committee-(NTSC) to convert the color image to grayscale is the rule as specified by Eq. (2.1) [25].

$$I = 0.2989R + 0.5870G + 0.1140B \tag{2.1}$$

This method may result in the loss of discriminative information inherent in the color image [2]. The pattern information conveyed by color discrimination is lost in the grayscale images transformed using the NTSC standard, as illustrated in the figure [35].

These images are also referred to be iso-luminous, Iso-luminous images exhibit consistent intensity values, with the information conveyed by variations in color [25] [35] .

The prominent characteristics indicated by color are absent when converted to grayscale using the traditional method (Fig 2.1). The features derived from the transformed grayscale images utilized for image classification influence the identification rate [2] [35].

The most straightforward and prevalent method utilizes the luminance channel (Y) of the CIE XYZ color space as the grayscale representation of the original color image (Cadik 2008[7]). Although this method is computationally efficient, it may be ineffective for iso-luminous images. Bala and Eschbach derived the grayscale variant of an image by incorporating the chrominance edge information, retrieved using a high-pass spatial filter, into the luminance channel to retain the discriminative details inherent in the original color image [6] [35].

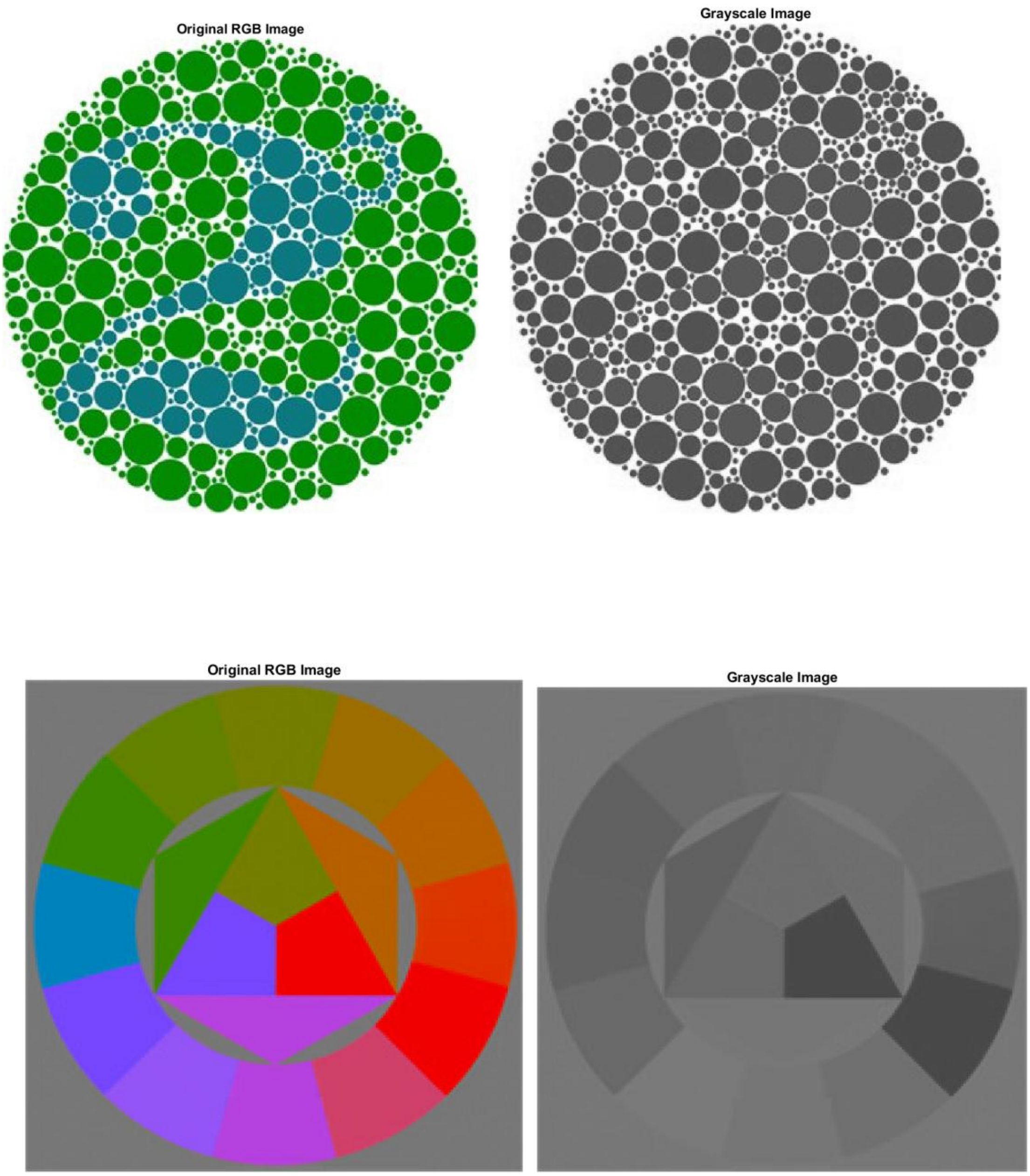


Fig 2.1: Iso-luminous color image and its Gray scale image by rgb2gry

Grundland and Dodgson (2007) suggested a method for global grayscale picture conversion. This work offered an image-independent parameter for controlling contrast enhancement. This approach is utilized to transform the color image into grayscale, from which the Feature descriptors are calculated for a hierarchical object recognition system [12]. A different image decolorization method with global mapping was introduced by Alsam and Drew (2009), A grayscale image is produced through a universal mapping to the image-independent gray axis. This method generates a crisp grayscale image by enhancement utilizing a mask [27].

Fig 2.2: Luma [25] based Grayscale Conversion

Fig 2.3: Grundland and Dodgson [12] based Grayscale conversion

A local image decolorization technique called 'Color2Gray' was introduced by Gooch, the gray value of each pixel is iterated to reduce the local contrast among all pixel pairs. The algorithm has significant computational complexity [11]. The Mantiuk (2006) study enhances the speed of the Color2Gray decolorization technique.

The acceleration of the Color2Gray algorithm is achieved by focusing solely on the pixel's neighbourhood at the finer levels of the pyramid [11].

The initial perceptual assessment of image decolorization algorithms was conducted by Cadik in 2008, the experimental design of the perceptual evaluation was conducted as follows: for each input image, seven techniques are assessed through one-to-one comparisons, specifically, for each input image, the number of comparisons is $(n\times(n-1)/2)$, where n represents the number of methods. utilized for the assessment. A total of 24 input photos exists, from which each observer randomly selects 8 images. The aggregate count of observers is 119 [7]. The total number of observations obtained is 19,992 (119 × 8 × 21). Two sorts of evaluation are conducted: accuracy and preference. The observer is instructed to choose the grayscale image that most accurately corresponds to the color's of the original image for accuracy evaluation, while for preference evaluation, the observer is asked to select the preferable grayscale image from the provided pair [35] [7].

The experimental results and analysis indicate that of the seven distinct approaches for image decolorization, the highest accuracy score was attained by Smith, while the most favoured methodology was proposed by Grundland and Dodgson (2007) [12] [7] [8].

The approaches with the lowest performance in terms of both accuracy and preference are those proposed by Bala and Eschbach (2004), this study demonstrates that no current picture decolorization algorithms yield universally satisfactory outcomes for all 24 input color images [6].

A decolorization method that effectively preserves dominant color variations from their surroundings was proposed by Ji. A group of band-pass filters changes the luminance into grayscale and these filters react best to locations with strong changes in color. The approach used for three-dimensional color images to grayscale is applied to multispectral images keeping high contrast detail. Drew (2009) [27] [7][35].

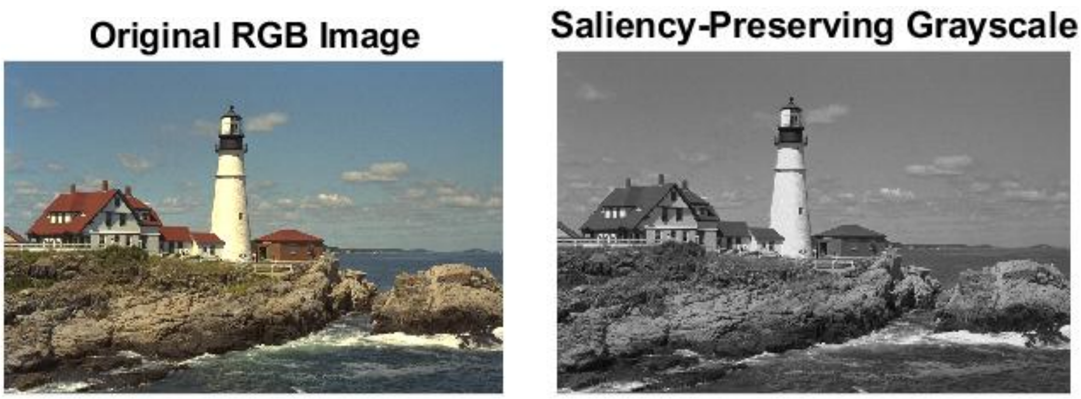


Fig 2.4: Gooch [11] based grayscale conversion.

Recent work has explored using SVD for grayscale conversion. In SVD-based methods, the RGB channels are decomposed into singular values, capturing the image's essential features. The grayscale value is derived from the norm of the diagonal matrix of singular values, weighted by a specific factor. This approach provides flexibility in adjusting contrast but can be computationally intensive and may still lose chromatic contrast under certain conditions [15].

Tabel :2.1 Comparison of Image Decolorization Methods.

Authors	Methods	Year	Advantages	Disadvantages
Gooch [11]	**Color2gray (**Salience-Preserving)	**2005**	Preserves color salience-via gradiant-based optimization	1)Computationally slow 2)Struggles with isoluminant regions
Grundland & Dodgson [12]	**Decolorize (**Contrast enhancement**)**	**2007**	1)Linear time complexity. 2)Real time Performance	May lose Global Contrast in Complex scenes
Smith [8]	**Apparent Grayscale (** Two-Step Global local mapping**)**	**2008**	1)Combines global lightnees mapping with local contrast 2)Perceptually accurate	1)Complex parameter tuning 2)Slower than basic methods
Kim [32]	**Nonlinear Global Mapping (**CIELab - based optimization**)**	**2009**	1)Robust to isoluminant regions. 2)preserves color order.	1)Requires manual parameter adjustments. 2)not real-time.

Lu [9]	**Real-Time Contrast Preserving (**Bimodal energy function**)**	**2012**	1)Balances speed and quality 2)linear parametric model.	1)Limited to local contrast. 2)may introduce artifacts.
T. Nguyen [33]	**Modulation Domain QP (**Quadratic programming with AM-FM features**)**	**2015**	1)Preserves local color distances. 2)polynomial-time complexity.	1)Computationally heavy for high-res images. 2)sensitive to noise
Neumann [7]	**Perception-Based Gradient Integration (**Coloroid system**)**	**2007**	1)Efficient gradient-field integration 2)preserves luminance-chrominance contrasts.	1)Struggles with smooth color transitions. 2)artifacts in textured regions.
Ancuti [15]	**Multi-Scale Fusion (**Information-theoretic weights**)**	**2015**	1)Reduces distortions via entropy-based weighting 2)multi-scale fusion.	1)High memory usage. 2)slow for large datasets.
Wu [34]	**Interactive Two-Scale (**Perceptual group decomposition**)**	**2012**	1User-adjustable gray tones. 2) preserves Gestalt principles.	Requires manual intervention 2)not fully automated.

2.1.1 Key insights from the Table:

- Grundland (2007) and Lu (2012) prioritize real-time performance but may sacrifice global contrast or introduce artif acts [9][12].

- Kim (2009) and Nguyen (2015) focus on accuracy but require higher computational resources [32][33].
- Gooch (2005) and Kim (2009) explicitly address isoluminant regions but differ in methodology (gradient-based vs. nonlinear mapping) [11][32].

- Smith (2008) and Wu (2012) allow user interaction for artistic adjustments but increase complexity [8][34].
- Modern methods (e.g., Lu 2012) use objective metrics like gradient recall ratio (GRR), while older techniques rely on perceptual studies [12].

“Independent Component Analysis (ICA) is a statistical method used to separate a multivariate signal into independent components”, Unlike SVD, which focuses on orthogonal decomposition, ICA aims to maximize the statistical independence between components. Applying ICA to RGB channels allows for the extraction of independent features, which can be used to generate grayscale images that retain more perceptual information and chromatic contrast. Despite its potential, ICA has been underexplored in the context of color-to-grayscale conversion, presenting a promising research direction. We also used the advantages of PCA by applying it to the ICA output and find the maximum Variations, and selecting the first principal component which will have more information. And normalizing it to obtain Gray Scale image. We also CLAHE on the obtained gray scale to get better contrast image.

Our proposed method leverages ICA & PCA Fusion to address the limitations of traditional Methods, offering a balance between computational efficiency and visual quality.

CHAPTER 3

METHODOLOGY

This suggested technique mixes ICA and PCA in a statistical way to take out color information from an image. Grayscale conversion attempts to keep important visual elements from the original image, all while minimizing image quality loss. Using a combination of advanced approaches, the suggested method enhances visual and statistical quality, as demonstrated by NIQE and PIQE scores.

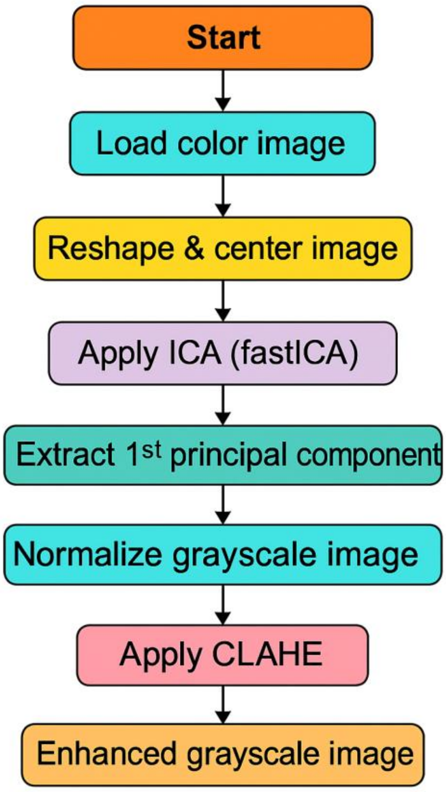


Figure 3.1: Flowchart

Algorithm of ICA-PCA Image Decolorization:

Input: RGB IMAGE

Output: Enhanced grayscale image

Step-1: Read input color image and convert to double precision

Step-2: Flatten the image into a 2D matrix of size [(m×n) x 3]

Step-3: Center each channel by subtracting the mean.

Step-4: Apply Independent Component Analysis (ICA) to extract 3 independent color components.

Step-5: Apply Principal Component Analysis (PCA) to the ICA components

Step-6: Select the first principal component as grayscale output.

Step-7: Normalize grayscale image to [0, 1].

Step-8: Apply CLAHE to enhance local contrast.

Step-9: Display final Enhanced grayscale image.

An RGB color image has three color channels Red, Green, and Blue. At each pixel location, the color is a linear combination of these three components. The goal is to derive a single grayscale channel that preserves the most meaningful information from all three.

We first reshape the image from a 3D array (height × width × 3) into a 2D matrix, where each row corresponds to a pixel, and each column corresponds to an RGB channel. Before applying ICA or PCA, the data is **centered** by subtracting the mean of each column (R, G, B): This ensures that both ICA and PCA operate on zero-mean data, which is a key assumption for these methods.

ICA decomposes the mixed RGB signals into **statistically independent components**. In the context of images, ICA aims to discover the **underlying sources** that give rise to the observed color mixtures.

When we apply ICA:

- We obtain three independent components (ICs), each representing a latent color structure or feature that is statistically independent from the others.
- These ICs capture edges, textures, or color features that are **not linearly correlated**.

While ICA gives us multiple independent components, **we cannot simply stack or**

display all three we want to produce **a single grayscale image**.

so we apply **PCA** on the ICA components to determine **which of these components (or their combination)** contains the **most variance**, i.e., **the most "useful" or "informative" signal** in terms of human visual perception.

Although ICA provides three independent channels, and PCA could yield multiple principal components, only **the first principal component (PC1)** is chosen because:

- It represents the **most dominant feature** across all pixels.
- It serves as a **compressed, yet information-rich projection** of the data.
- Human visual perception is primarily sensitive to **intensity contrast**, which PC1 best captures after ICA filtering

This Grayscale image is then optionally enhanced (e.g., using CLAHE) and evaluated for quality using metrics like NIQE or PIQE.

3.1 Independent Component Analysis:

A strong and adaptable method for data analysis, independent component analysis (ICA) provides a distinctive viewpoint on the investigation and discovery of hidden patterns in intricate datasets. Fundamentally, ICA is a signal processing technique that aims to divide a collection of mixed signals into statistically independent parts, offering priceless insights and applications across a range of fields [31].

Discovering important facts among a lot of less significant data is necessary today. ICA is necessary in this situation since it allows us to know which form of data contributes the most, even if not every part of the mixing is explained. In image processing, speech recognition, finance and medical research, ICA helps people deal with complex data structures.

3.1.1 Blind Source Separation.

The field is known for putting importance on blind separation of sources. This comes up when you do not know what the sources are and all you can access are the mixed versions of the signals. Because such situations are like solving a changed puzzle with missing pieces, ICA offers hope to struggling researchers and analysts [31].

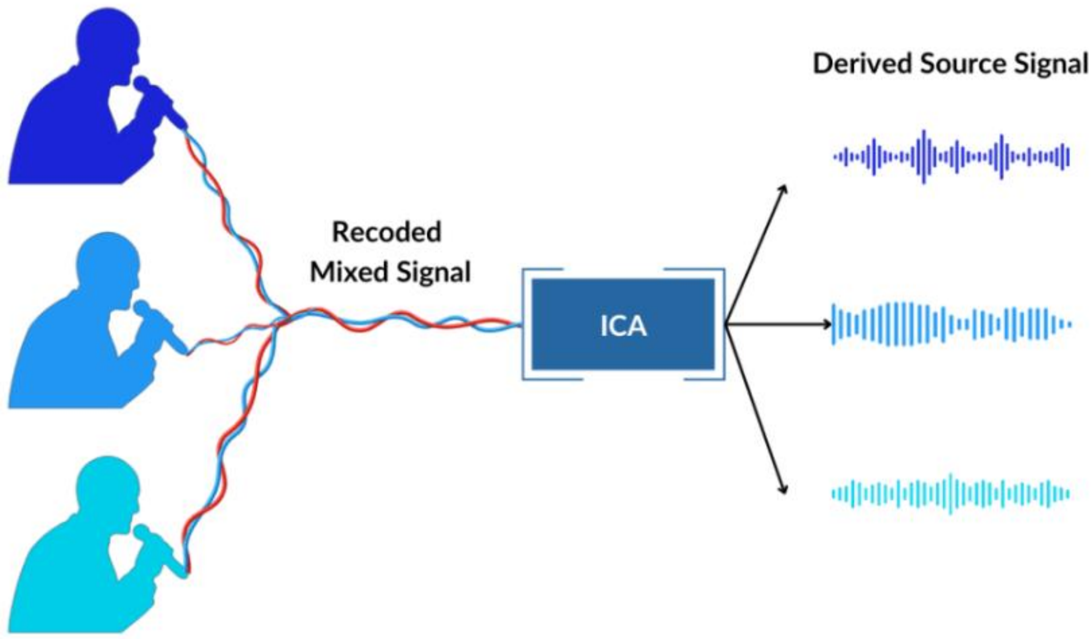


Fig 3.2 : Blind Source Separation

To find the basic signals, you first have-to-reverse engineer the mixed ones.

Independent component analysis is a suitable way to discover patterns and independent sources within mixed data structures. Whether applied to neuroimaging, the analysis of images or processing signals, ICA has been very efficient at uncovering hidden components and giving useful results. Both experts and readers should understand the issues and boundaries of ICA such as the need for data to be independent and non-Gaussian, problems with large data sets and difficulties with the meaning of components.

Despite these challenges, ICA is still a key technique for data analysis as it helps analysts and researchers improve their data, make analysis easier and tell different types of sources apart. Vectors are applied in financial data analysis, audio source separation and medical imaging. Proposals in non-negative ICA and their partnership with deep learning can deal with present challenges and make ICA more widely used.

In order to effectively use ICA in practice, you need to know the domain, preprocess the data, choose components with care and carefully evaluate the main assumptions and issues. While ICA may not solve every problem, using it properly can really help make sense of challenging data sets and reveal useful facts [32].

Anyone using ICA should study its strengths and weaknesses carefully and follow its principles while keeping the needs of the assignment in mind; the same should apply to any data analysis method. Because of this, analysts and researchers can take advantage of ICA to find patterns, improve data analysis and achieve important results in many areas.

3.2 Principal component Analysis:

PCA, a statistical technique, turns the original variables into PCs which are not correlated.

Imagine wishing to view a collection of 3D points on a level 2D surface. PCA determines the optimal plane for flattening data while preserving most of its structure [30].

Step-by-Step PCA Process [30]:

Step-1: Standardize the data.

Ensure all features have mean = 0 and standard deviation = 1

$$X_{\text{scaled}} = \frac{X - \mu}{\sigma} \tag{3.1}$$

Step-2: Compute the covariance matrix.

$$\text{Cov}(X) = \frac{1}{n-1} X^T X \tag{3.2}$$

Where,

X - Standardized data Matrix

N - number of samples

Step-3: Find Eigen Values and Eigen Vectors.

$$\text{Cov}(X) \cdot v = \lambda \cdot v \tag{3.2}$$

Where,

v is Eigen Vector (Principal Direction)

λ is Eigen Value (Variance Explained)

Step-4: Select Top K Principal Component.

Choose a K eigen vector with Strogest eigen value.

The Explained Variance ratio shows us how much information is kept.

$$Explained\ Variance\ Ratio\ =\ \lambda_k/(\sum^{n}{}_{i}{}^{=1}\lambda_i) \qquad (3.4)$$

Step-5: Transforming the data

Projecting the data into new axis (principal component)

$$X_{\mathrm{PCA}} = X \cdot W \qquad (3.5)$$

Where w is matrix of k top eigen vector.

X_{PCA} is the reduced dimension dataset.

3.3 CLAHE

In digital image processing, histogram equalization is a popular method for contrast enhancement. However, traditional global histogram equalization often leads to over-enhancement and loss of local image details, especially in images with varying illumination. To address this limitation, Contrast Limited Adaptive Histogram Equalization (CLAHE) is employed. CLAHE is an extension of Adaptive Histogram Equalization (AHE), designed to improve local contrast while avoiding noise amplification.

3.3.1 Working Principle CLAHE

CLAHE operates by dividing the input image into small rectangular regions called **tiles** (e.g., 8×8 blocks). For each tile, it computes a histogram and applies histogram equalization locally. The key differentiating steps of CLAHE are:

- **Adaptive Local Processing**:
  - Each tile is processed independently.
  - This ensures that local contrast is enhanced even in low-contrast regions (e.g., shadows or hazy areas).
- **Histogram Clipping (Contrast Limiting)**:

- To prevent over-amplification of noise (common in flat or uniform regions), CLAHE introduces a **clip limit**.
- Any histogram bin that exceeds the clip limit is clipped, and the excess is redistributed uniformly to all histogram bins
- This step **limits noise** and **controls the amplification** of undesired features.

➢ **Bilinear Interpolation**:
- After equalizing each tile, CLAHE uses **bilinear interpolation** to combine neighbouring tiles and eliminate artificially induced boundaries.
- This blending ensures a **smooth transition** between tiles and avoids artifacts.

CHAPTER 4

RESULTS AND ANALYSIS

4.1 Dataset and Tool Requirements.

The dataset utilized for evaluating and comparing the proposed methodology is Cadik.M, CSDD. The implementation of the proposed methodology was conducted on MATLAB Software and the Version Used is 2023a.

4.2 Blind Quality Assessment.

The primary issue with measuring image quality is “no-reference image quality, also known as blind image quality,” which lacks prior information of the type of distortion. It has long been a difficult research topic to evaluate an image's quality without a reference since different kinds of distortion might result in wildly different image content. Additionally, the research community is very interested in picture quality assessment because of the increasing quantity and importance of digital images in our daily life [23].

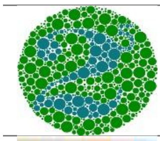
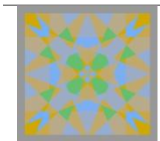
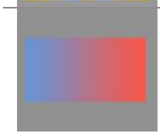
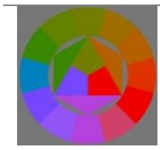
Two well-known methods in this area are the:

- “Psychovisually-based-Image-Quality-Evaluator (PIQE)”
- “Natural Image Quality Evaluator (NIQE)”

Without being exposed to distortion or trained on human-rated distorted images, the NIQE evaluates departures from statistical regularities in natural images. NIQE uses a default model that is based on photographs of natural scenes to assess an image's perceptual quality. A lower score denotes a higher-quality image [16].

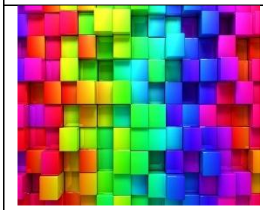
On the other hand, good quality is indicated by a low score [16]. In this study, we compared the quality of color image conversion techniques using NIQE and PIQE. The NIQE and PIQE values did not accurately represent the quality of the images; rather, they may be approximations since we did not improve the images prior to conversion (images may suffer from noise, blurring, etc.).

Table4.1: Comparison of Quality Metrics [16].

Original Image	Quality metric	Gooch	Grundland	Smith	Kim	Lu	T. Nguyen	Proposed
	NIQE	5.68	7.50	7.09	6.51	6.20	6.75	4.02
	PIQE	28.21	29.05	27.41	43.16	24.41	28.61	31.37
	NIQE	3.58	3.30	3.40	3.61	3.27	3.42	3.31
	PIQE	43.62	42.30	43.10	52.75	44.40	43.88	30.10
	NIQE	10.77	10.69	8.13	7.58	10.41	10.82	7.53
	PIQE	63.16	64.88	46.05	52.72	65.21	64.24	65.91
	NIQE	24.89	26.08	19.77	23.85	40.16	24.39	18.41
	PIQE	81.22	81.83	84.50	80.32	77.60	80.80	47.47
	NIQE	5.90	5.30	5.65	5.62	5.70	5.98	5.8022
	PIQE	50.07	54.11	55.44	72.46	52.73	55.25	34.152
	NIQE	11.20	10.25	7.46	6.82	11.21	11.73	9.56
	PIQE	79.74	79.53	70.60	66.29	79.57	80.84	69.89
	NIQE	10.07	11.04	9.76	9.82	12.06	10.64	24.84
	PIQE	92.14	100.0	90.50	100.0	100.0	100.0	66.18
	NIQE	9.15	9.01	7.50	7.58	9.23	8.81	8.398
	PIQE	81.46	83.78	79.56	79.76	82.66	81.56	57.30

The above table was calculated based on Cadik.M publicly available data set [7]. As shown in Table 1, the proposed method consistently achieved **lower NIQE and PIQE values** across various test images, indicating superior naturalness and perceptual fidelity.

Table 4.2 Quality metrics on CSDD dataset.

Original Image	Quality metric	Rgb2gray	Proposed
	NIQE PIQE	4.26 73.67	3.25 44.47
	NIQE PIQE	2.76 35.25	2.56 31.86
	NIQE PIQE	3.78 48.99	3.25 45.22
	NIQE PIQE	3.15 32.67	3.1 32.0
	NIQE PIQE	3.07 33.02	2.73 32.21
	NIQE PIQE	3.40 32.22	2.69 31.15
	NIQE PIQE	2.88 18.66	2.72 15.38

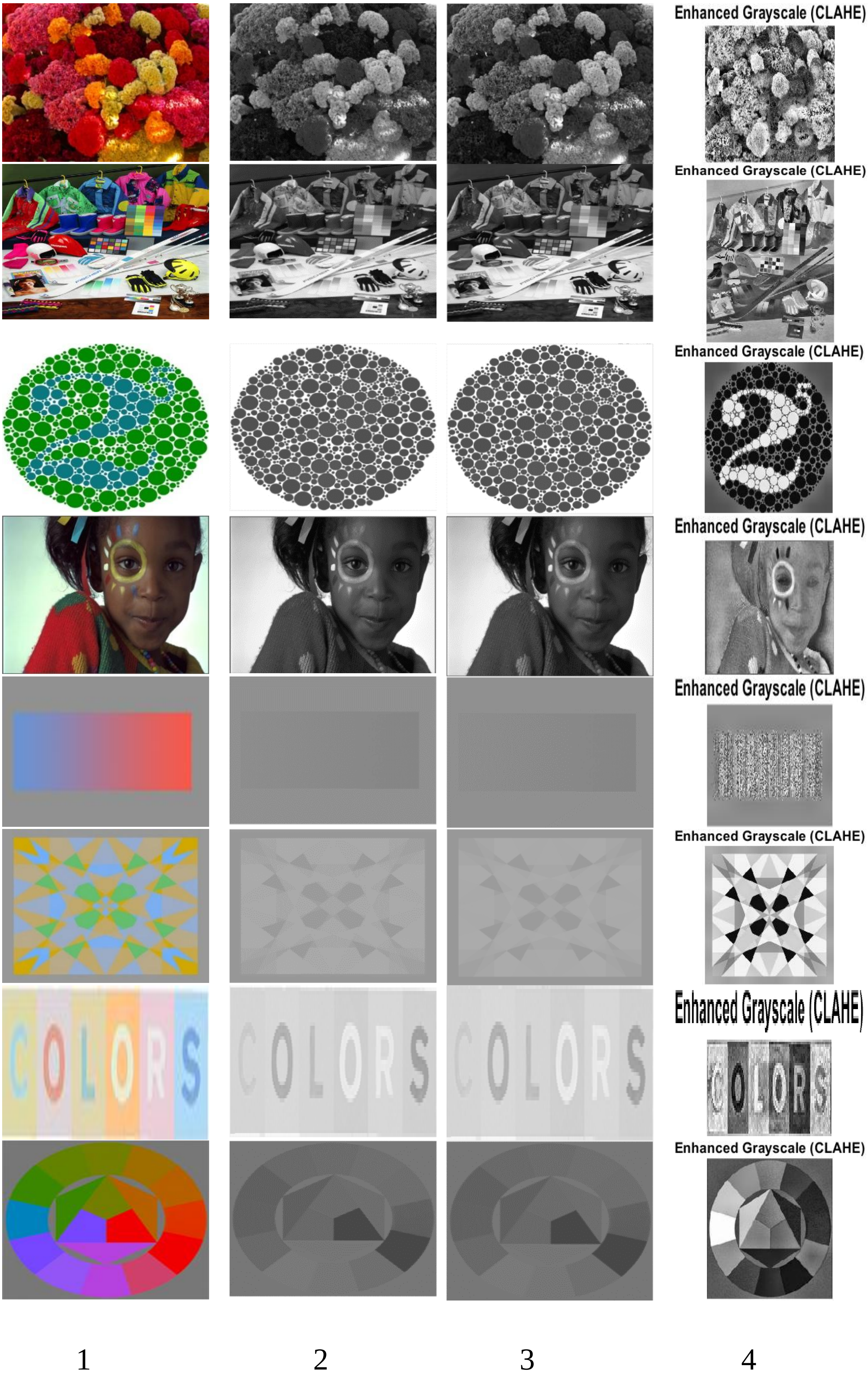


Fig 4.1: 1. Original image, 2. MATLAB Grayscale Image, 3. Luma based Grayscale image, 4. Proposed Method Grayscale Image

Finally, the quality of the obtained decolorized images using different methods was compared and is presented in Table 1. It is evident from the table that **the proposed ICA + PCA fusion-based method** achieves superior perceptual quality compared to other techniques. Unlike traditional grayscale conversion methods that often overlook the statistical independence and significance of color channels, the proposed method leverages the strengths of Independent Component Analysis (ICA) to extract independent features from the RGB image and applies Principal Component Analysis (PCA) to prioritize the most visually informative components. Because of this, viewers get a more accurate gray image, as shown by enhanced results on the NIQE and PIQE evaluation methods. The improved gray-level images hold onto important details, so the results look better and can be used in computer vision applications.

Comparing the results using my eyes shows that preserving edges and textures works more efficiently with my method than most earlier methods. The created grayscale images are like color images in terms of importance and are thus more useful for finding objects, outlining objects, and preparing images for use in computer vision.

To improve the technique's consistency, we made sure that the computer did not use a different random seed each time by using rng ('default'). Consequently, the approach guarantees uniform results and consistent quality scores over several tests which has not been possible in earlier environments with ICA-based decolorization methods.

CHAPTER 5
CONCLUSION AND FUTURE SCOPE

5.1 Conclusion

In this thesis, a new method for generating grayscale images from color images has been introduced and evaluated using Independent Component Analysis (ICA) and Principal Component Analysis (PCA). The primary goal was to enhance the quality of grayscale images by employing a method that considers both the statistical independence and the visual significance of color channels. The process involves first decomposing RGB images using ICA into statistically independent components, followed by projecting these components onto the axis that retains the most meaningful information using PCA. After generating the grayscale image, Contrast Limited Adaptive Histogram Equalization (CLAHE) was applied to enhance contrast and improve visual clarity.

The analysis showed that the proposed method outperformed Greyish Decolorize, Color2Gray, Apparent Grayscale, and several other leading alternatives. The grayscale outputs produced by the method were more faithful in terms of structure and texture, resulting in images that were both visually clearer and better suited for further processing with image analysis tools.

Along with the scores, a visual assessment proved the method's power to preserve important features in the stimuli. Because a fixed random seed was added, each run produced the same moment-to-moment results, overcoming the random differences present in other ICA applications.

To conclude, using the fusion-based approach by ICA and PCA has led to a promising progress in the image decolorization process by successfully combining computational simplicity and excellent end results

5.2 Future Scope

The approach seems to lead to improved results, yet there are many directions we could investigate to take this research further:

- **Real-time Implementation:**

  The current MATLAB implementation can be optimized for real-time applications using parallel computing or GPU acceleration, making it suitable for live video decolorization in surveillance or assistive technologies.

- **Deep Learning Integration:**

  Future work can investigate hybrid models that combine deep learning techniques (e.g., convolutional autoencoders or GANs) with ICA-PCA features to learn more complex perceptual mappings for grayscale conversion.

- **Application-Specific Optimization:**

  Custom versions of the algorithm could be developed for specific applications such as medical imaging, remote sensing, or content-aware grayscale printing, where preserving certain features is more critical than overall appearance.

- **Extension to Color Vision Deficiency (CVD) Support:**

  Enhancing the method to accommodate color-blind viewers by embedding saliency or contrast information targeted at individuals with CVD could make grayscale images more accessible.

- **Multi-scale Feature Extraction:**

  Introducing multi-scale decomposition (e.g., wavelet transforms or Laplacian pyramids) before ICA could enable better capture of global and local features for more detailed grayscale synthesis.

- **Subjective User Studies:**

  While objective metrics were used in this thesis, conducting **user-based subjective evaluations** can provide additional insights into human-perceived quality and usability of the decolorized images.

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