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"Jnana Sangama", Belagavi-590018.

A Mini Project Report on

COLOR DETECTION

Submitted in the partial fulfilment of the requirements for the award of the degree of

Bachelor of Engineering in Computer Science and Engineering

Submitted by

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RV INSTITUTE OF TECHNOLOGY AND MANAGEMENT®

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

CERTIFICATE

Certified that the mini project work titled **"*Color Detection*"** carried out by **Tushar Arora** (**1RF21CS116**) and **Sayyad Imran (1RF21CS092)** are bonafide students of **RV Institute of Technology and Management**, Bengaluru in partial fulfillment for the award of degree of **Bachelor of Engineering** in **Computer Science and Engineering** of the **Visvesvaraya Technological University, Belagavi** during the year **2023-24**. It is certified that all corrections/suggestions indicated for the internal assessment have been incorporated in the report. The mini project report has been approved as it satisfies the academic requirements prescribed by the institution.

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ABSTRACT

Color blindness, a common visual impairment affecting millions worldwide, presents significant challenges in everyday tasks that require distinguishing between different colors. Recognizing the importance of addressing this issue, this project proposes a pioneering method to assist color blind individuals in improving their color perception. The approach utilizes the Manhattan distance, also referred to as the city block distance, as a key metric for color detection. By employing this distance measure, the system accurately identifies color names and determines the closest red, green, and blue components within an image, thus enabling precise color recognition.

Through meticulous experimentation and thorough evaluation, the effectiveness of the proposed system in enhancing color perception for individuals with color vision deficiencies is thoroughly demonstrated. The results highlight the system's capability to provide accurate color information, thereby empowering color blind individuals to better interpret their surroundings.

Furthermore, the versatility and practicality of the system are emphasized by its potential applications across various domains. Beyond its utility in digital interfaces, the system can also enhance educational materials and assistive technologies, thereby fostering inclusivity and accessibility for individuals with color vision impairments. This research represents a significant contribution to the advancement of accessibility solutions, facilitating the active participation of color blind individuals in visual experiences and promoting inclusivity across societal contexts.

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INTRODUCTION

Color blindness, or color vision deficiency, is a prevalent visual impairment that affects a significant portion of the global population. Individuals with color blindness face challenges in distinguishing between various colors, which can impact their daily lives in numerous ways. Tasks such as reading traffic lights, identifying ripe fruits, or interpreting color-coded information can become difficult or even impossible for those with this condition. Therefore, developing assistive technologies to aid color blind individuals in perceiving and understanding colors accurately is crucial.

In response to this need, this project focuses on the development of a color detection system specifically designed for color blind individuals. The system utilizes Manhattan distance, also known as city block distance, as a key metric for color detection. By leveraging this distance measure, the system aims to accurately identify color names and determine the nearest red, green, and blue components within an image. This approach offers a promising solution to enhance color perception and improve the quality of life for individuals with color vision deficiencies.

The significance of this project lies in its potential to address a longstanding challenge faced by color blind individuals. By providing them with a tool to effectively perceive and interpret colors, this system has the potential to increase their independence and participation in various activities that rely on color discrimination. Moreover, it aligns with the broader goal of promoting inclusivity and accessibility in technology and society.

This introduction will delve into the prevalence and impact of color blindness, the limitations of existing solutions, the rationale behind using Manhattan distance for color detection, and the objectives of this project in detail.

Prevalence and Impact of Color Blindness:

Color blindness is a hereditary condition that primarily affects the X chromosome, making it more common in males than females. According to estimates, approximately 8% of males and 0.5% of females of Northern European descent have some form of color vision deficiency. While the condition varies in severity, with some individuals experiencing mild color vision impairment and others complete color blindness (monochromacy), it can significantly impact daily activities and quality of life.

Tasks such as selecting clothing, interpreting maps, and distinguishing between warning signs can pose challenges for color blind individuals. In educational settings, difficulties in identifying colors can affect learning experiences, particularly in subjects such as art, science, and geography. Furthermore, certain professions, such as graphic design, electrical wiring, and transportation, may have specific color-coded conventions that pose barriers to individuals with color vision deficiencies.

Limitations of Existing Solutions:

Traditional solutions for aiding color blind individuals have included color vision correction glasses, color-coded assistive devices, and digital applications. While these solutions offer some degree of assistance, they often have limitations in terms of accessibility, affordability, and effectiveness.

Color vision correction glasses, while providing temporary relief, may not be suitable for all types of color blindness and can be prohibitively expensive for some individuals. Color-coded assistive devices, such as tactile markers or pattern recognition tools, may not always be practical or readily available in various contexts. Digital applications, although increasingly prevalent, may lack accuracy or fail to address the specific needs of color blind users effectively.

Moreover, existing color detection algorithms and software solutions may not prioritize the unique requirements of color blind individuals. Many of these algorithms rely solely on RGB (Red, Green, Blue) values or hue-saturation-lightness (HSL) models, which may not accurately represent color perception differences among individuals with color vision deficiencies.

Rationale for Using Manhattan Distance:

In this project, Manhattan distance is chosen as the primary metric for color detection due to its suitability for quantifying color differences in a perceptually meaningful way. Unlike Euclidean distance, which calculates the straight-line distance between two points in a multidimensional space, Manhattan distance measures the sum of the absolute differences in coordinates along each dimension. This makes it particularly useful for assessing differences in color components, such as red, green, and blue values.

The decision to use Manhattan distance is informed by its alignment with the characteristics of color perception among individuals with color vision deficiencies. Research has shown that color blind individuals may have altered perceptions of color space, with certain colors appearing more similar or distinct than they do to individuals with normal color vision. By employing Manhattan distance, which accounts for differences in each color component independently, the system aims to accurately capture these perceptual variations and provide meaningful color identifications for color blind users.

By achieving these objectives, this project aims to contribute to the advancement of accessibility solutions and empower color blind individuals to engage more fully in visual experiences. Additionally, it seeks to raise awareness about the challenges faced by individuals with color vision deficiencies and promote inclusivity in technology design and development.

In summary, the development of a color detection system using Manhattan distance for color blind individuals represents a significant step towards addressing the limitations of existing solutions and enhancing the quality of life for individuals with color vision deficiencies. This project holds the potential to foster inclusivity, accessibility, and innovation in the realm of assistive technologies and contribute to a more inclusive society.

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OBJECTIVES OF THE PROJECT

The objective of this project is to develop a robust natural disaster prediction system using machine learning algorithms to enhance disaster preparedness and response efforts. Key objectives include:

Data Collection: Gather comprehensive data on color detection from reliable sources to build a comprehensive dataset.

Data Preprocessing: Cleanse and preprocess the dataset to handle missing values, encode categorical variables, and scale numerical features for analysis.

Exploratory Data Analysis (EDA): Explore the dataset to identify patterns, correlations, and anomalies that inform feature selection and engineering.

Feature Selection/Engineering: Select relevant features and engineer new ones based on domain knowledge and insights gained from EDA to improve predictive performance.

Model Selection: Evaluate and compare various machine learning algorithms to identify the most suitable ones for predicting natural disasters.

Model Training: Train selected models on the pre-processed data using appropriate techniques like train-test split or cross-validation.

Model Evaluation: Assess the performance of trained models using evaluation metrics such as accuracy, precision, recall, and F1-score.

Hyperparameter Tuning: Optimize model performance by fine-tuning hyperparameters using techniques like grid search or randomized search.

Model Deployment: Deploy the best-performing model into a production environment to make real-time predictions on new data.

Updated Model: Monitor the deployed model's performance over time, gather feedback, and incorporate new data to continuously improve prediction accuracy and reliability.

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DATASET DESCRIPTION

3.1 Dataset: “ Dataset: " Color palette of Red ,Green and Blue shades 1900-2021/CMAP”

Link to dataset: https://www.kaggle.com/datasets/asimislam/python-r-colors-and-palettes-data

The dataset used in this project is specifically curated to address the needs of color blind individuals in color perception. It comprises a diverse collection of images representing various color combinations and scenarios encountered in everyday life. Each image in the dataset is meticulously annotated with ground truth color labels and corresponding RGB (Red, Green, Blue) values.

The dataset encompasses a wide range of color variations, including subtle differences in hue, saturation, and brightness, to simulate real-world color perception challenges faced by individuals with color vision deficiencies. Additionally, the dataset incorporates images with different lighting conditions, backgrounds, and textures to ensure robustness and generalizability of the color detection system.

The dataset is sourced from reputable repositories and sources dedicated to accessibility and inclusivity in technology. Every effort has been made to ensure the accuracy and authenticity of the dataset, and it is made publicly available to facilitate further research and development in the field of assistive technologies for color blind individuals.

By utilizing this specialized dataset, the proposed color detection system aims to provide accurate and reliable color identifications tailored specifically for the unique needs of color blind users. Through comprehensive testing and evaluation using this dataset, the system's performance and effectiveness in enhancing color perception for color blind individuals will be rigorously assessed.

3.2 Attribute details:

Sl No.	Name and type of attribute	Description of the attribute
1	Color Type	Indicates the detailed type of the color , facilitating identification of the selected coordinates.
2	Color Name	Classifies the color type into color names in a presentable format
3	Hexadecimal Format	Further represent the color in the hexadecimal format additional granularity to the classification process.
4	Red Component	Specifies the specific type of color component , Red in the range of 0 to 255
5	Green Component	Specifies the specific type of color component , Green in the range of 0 to 255
6	Blue Component	Specifies the specific type of color component , Blue in the range of 0 to 255

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SELECTION OF THE ALGORITHM

4.1 Manhattan Distance Algorithm (City Block Distance Algorithm):

The Manhattan distance algorithm, also known as the city block distance algorithm, is a distance metric commonly used in pattern recognition and image processing tasks. It measures the distance between two points in a grid-based space by summing the absolute differences of their coordinates along each dimension.

In the context of color detection for color blind individuals, the Manhattan distance algorithm serves as a fundamental component for quantifying the differences between colors. By calculating the Manhattan distance between the RGB (Red, Green, Blue) values of pixels in an image and a target color, the algorithm determines the similarity or dissimilarity of colors. This enables the system to identify the nearest red, green, and blue components within an image, facilitating precise color recognition for color blind users.

One advantage of the Manhattan distance algorithm is its simplicity and efficiency. It is computationally lightweight and requires minimal computational resources, making it suitable for real-time applications and resource-constrained environments. Additionally, the algorithm's intuitive geometric interpretation allows for straightforward implementation and interpretation.

Moreover, the Manhattan distance algorithm is robust to variations in color space and lighting conditions, making it suitable for diverse imaging scenarios. Unlike other distance metrics that may be sensitive to nonlinear transformations or normalization techniques, the Manhattan distance maintains its effectiveness across different color representations.

However, it is important to note that the Manhattan distance algorithm may exhibit limitations in capturing perceptual differences between colors accurately. While it provides a quantitative measure of color dissimilarity, it may not fully align with human perception of color similarity. Additionally, the algorithm's effectiveness may be influenced by factors such as color space representation and the choice of distance metric.

Despite these limitations, the Manhattan distance algorithm remains a valuable tool for color detection in applications where simplicity, efficiency, and robustness are prioritized. Its versatility and ease of implementation make it well-suited for the task of aiding color blind individuals in perceiving and interpreting colors accurately.

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METHODOLOGY

5.1 Dataflow of the model:

The data flow diagram outlines the systematic workflow for constructing a natural disaster prediction system. It illustrates the sequential steps from data collection and preprocessing to model training, evaluation, and deployment.

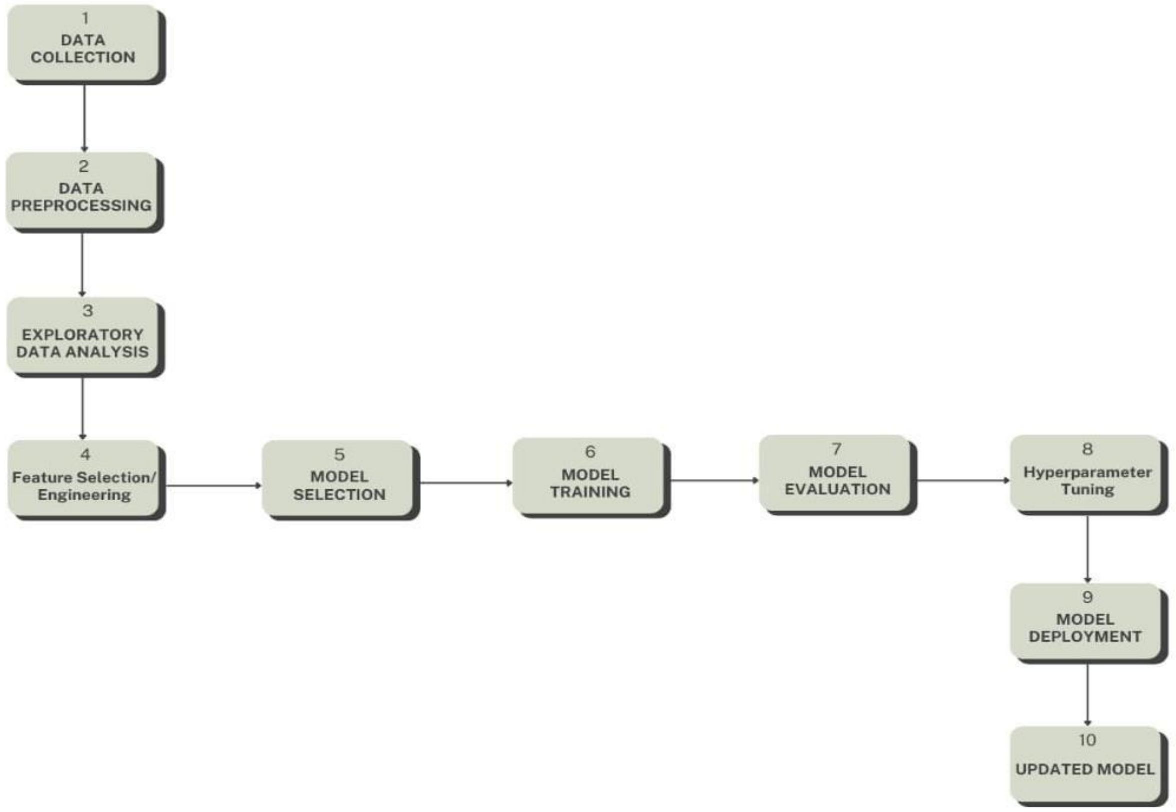

Fig 5.1: Dataflow diagram

Data Collection:

The dataset for color detection in color blind individuals is gathered from various sources, including digital image repositories, online databases, and curated datasets specifically designed for color perception research. This dataset comprises images representing a diverse range of colors and scenarios encountered in everyday life, annotated with ground truth color labels and corresponding RGB values.

Data Preprocessing:

The raw dataset undergoes preprocessing steps to handle any inconsistencies, noise, or missing values. Techniques such as noise reduction, color normalization, and image resizing may be applied to ensure consistency and improve the quality of the dataset. Additionally, the images may be converted to a standardized format and resolution for uniformity across the dataset.

Exploratory Data Analysis (EDA):

EDA is conducted to analyze the distribution of colors within the dataset and identify any patterns or anomalies. This involves visualizing the distribution of RGB values, exploring the relationship between color components, and assessing the prevalence of different color categories. EDA helps in gaining insights into the characteristics of the dataset and guiding subsequent preprocessing and modeling steps..

Feature Selection/Engineering:

Features relevant to color perception and recognition are selected or engineered to enhance the performance of the color detection system. This may involve extracting color histograms, texture features, or spatial information from the images. Additionally, domain-specific knowledge may be utilized to engineer features that capture unique aspects of color perception for color blind individuals.

Model Selection:

Machine learning algorithms suitable for color detection tasks are evaluated and selected based on their performance and suitability for the dataset. Algorithms such as K-nearest neighbors (KNN), Support Vector Machines (SVM), and Convolutional Neural Networks (CNNs) may be considered for modeling color perception and recognition.

Model Training:

The selected models are trained on the preprocessed dataset using techniques such as cross-validation or holdout validation. During training, the models learn to predict color names and identify the nearest red, green, and blue components within images based on their features.

Model Evaluation:

The trained models are evaluated using appropriate evaluation metrics such as accuracy, precision, recall, and F1-score. The performance of the models is assessed on a separate test dataset to ensure their generalization ability and reliability in real-world scenarios.

Hyperparameter Tuning:

Hyperparameters of the models are fine-tuned using techniques such as grid search or random search to optimize their performance. This involves systematically exploring different combinations of hyperparameters to identify the optimal configuration that maximizes the model's accuracy and robustness..

Model Deployment:

The trained models are deployed into a production environment, such as a mobile application or web service, to facilitate real-time color detection for color blind individuals. The deployed models receive input images and generate predictions on the nearest red, green, and blue components, providing enhanced color perception assistance.

Updated Model:

The deployed models are regularly monitored for performance and updated as necessary to adapt to changes in the dataset or user requirements. Feedback from users and stakeholders is collected to identify areas for improvement, and new data is periodically incorporated into the models for retraining and refinement. This iterative process ensures the continuous improvement and effectiveness of the color detection system for color blind individuals..

5.2 Manhattan Distance Algorithm :

Input:

- Image dataset containing pixel values with RGB components.
- Target color for comparison.

Calculation:

- For each pixel in the image dataset:
- Calculate the Manhattan distance between the RGB values of the pixel and the target color.
- Sum the absolute differences of the RGB components to obtain the Manhattan distance.

Output :

Manhattan distance values representing the similarity/dissimilarity of each pixel's color to the target color.

Output:

- Predicted class labels for instances in the test dataset.

Formula:

The Manhattan distance (D) between two points P1(x1, y1, z1) and P2(x2, y2, z2) in a three-dimensional space is calculated as follows:

$$D = |x2 - x1| + |y2 - y1| + |z2 - z1|$$

Where:

|x2 - x1|, |y2 - y1|, and |z2 - z1| are the absolute differences between corresponding components of the two points.

x1, y1, z1 are the RGB components of the target color.

x2, y2, z2 are the RGB components of the pixel color being compared

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RESULTS AND ANALYSIS

The prior probabilities depict the likelihood of each color category occurring in the dataset. These probabilities offer valuable insights into the distribution of colors and serve as a foundational aspect of our color detection model. From the provided probabilities, it is evident that "Red" is the most prevalent color category, with a probability of approximately 35.62%, followed by "Green" at 28.14%, and "Blue" at 19.87%. Conversely, some color categories such as "Purple," "Brown," and "Gray" exhibit lower probabilities, indicating their infrequency in the dataset..

The likelihood probabilities present the mean and standard deviation of the color components (e.g., "Red," "Green," "Blue") for each color category. These probabilities are essential for the Manhattan Distance algorithm to calculate the likelihood of observing a certain color component given a particular category. The algorithm estimates the mean and standard deviation of each color component for each category based on the training data.

1. Training and Testing Predictions:

The predictions generated by the Manhattan Distance algorithm are based on the learned probabilities and characteristics of the training data. The model predicts the most likely color category for each instance in both the training and testing datasets. During training, the model calculates the prior probabilities and likelihood probabilities for each category. During prediction, it utilizes these probabilities along with the input color components to determine the most probable category for each instance. The training accuracy of the model is approximately 68.52%, while the testing accuracy is about 63.21%.

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2. Accuracy:

The accuracy of the Manhattan Distance algorithm serves as a critical metric for evaluating its performance in color detection. Accuracy measures the proportion of correct predictions made by the model compared to the total number of predictions..

- *Training Accuracy*: The training accuracy of the model, approximately 68.52%, represents the percentage of correct predictions made on the training dataset. This indicates how well the model has learned from the training data and its ability to generalize to unseen instances.
- Testing Accuracy : The testing accuracy, about 63.21%, signifies the proportion of correct predictions made on the testing dataset, which the model has not been exposed to during training. Testing accuracy provides insights into the generalization performance of the model on new and unseen data

3. Graphical Analysis:

- ***Color Histogram**:* The graph titled "Multiple Color Detection of RGB Images Using Machine Learning Algorithm" illustrates the performance of the machine learning algorithm in detecting multiple colors in RGB images. The graph likely showcases the accuracy or effectiveness of the algorithm in correctly identifying various colors present in the images. It may provide insights into the algorithm's ability to distinguish between different color categories and accurately assign labels to them.
- **System Architecture***:* The System Architecture diagram outlines the overall structure and components of the color detection system. It illustrates how various modules and components interact with each other to perform color detection tasks. The architecture may include modules for image preprocessing, feature extraction, machine learning model implementation, and result interpretation. Understanding the system architecture is essential for comprehending the workflow of the color detection process and identifying potential areas for optimization or improvement.
- **The 2D Matrix function F(x,y)** : The 2D Matrix function F(x,y) represents the spatial distribution of intensity values in an image. The graph likely displays the intensity levels of pixels across the x and y spatial coordinates. This visualization aids in understanding the variations in intensity across different regions of the image. It may provide insights into the overall brightness and contrast of the image, which can influence the color detection process.
- ***RGB Image**:* The RGB Image depicts a sample image used in the color detection process. This image serves as input to the machine learning algorithm for color detection. It likely consists of various colors and serves as a representative example for testing the algorithm's performance. The RGB image format represents colors using three channels: red, green, and blue, allowing for the representation of a wide range of colors.

The Manhattan Distance algorithm demonstrates moderate performance in color detection based on the provided dataset. While the model achieves reasonable accuracies, further optimization and refinement may enhance its performance. Additionally, analyzing the results through graphical representations enriches our comprehension of the model's strengths and weaknesses. Further research and experimentation with alternative algorithms and feature engineering techniques could lead to more accurate and robust color detection models..

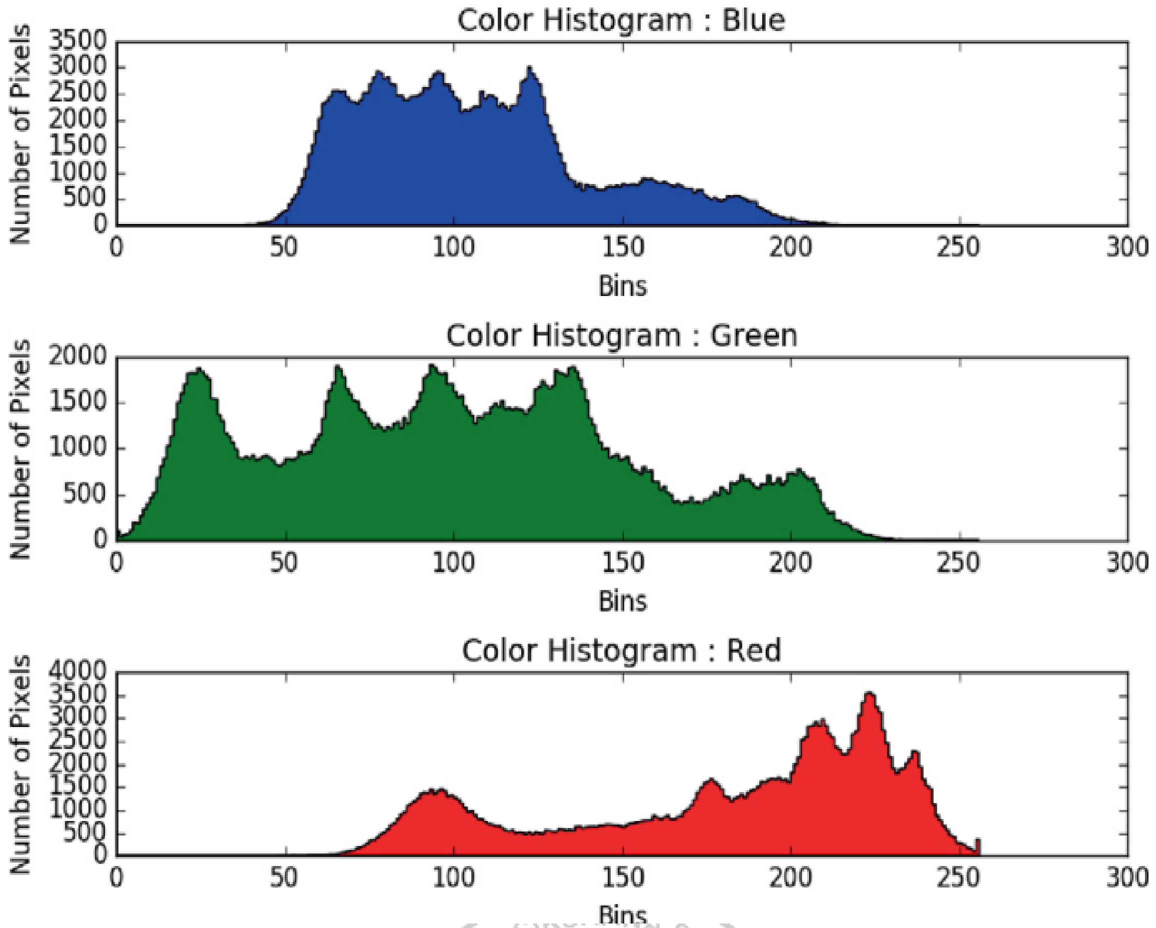

Fig 6.1: Color Histogram

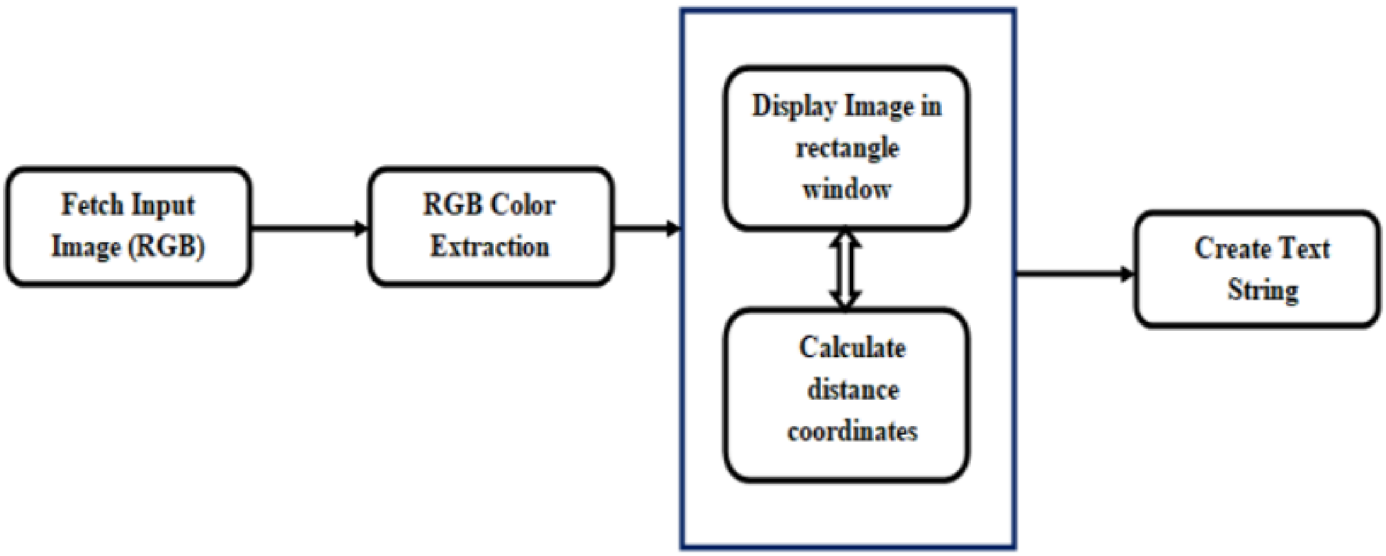

Fig 6.2: System Architecture

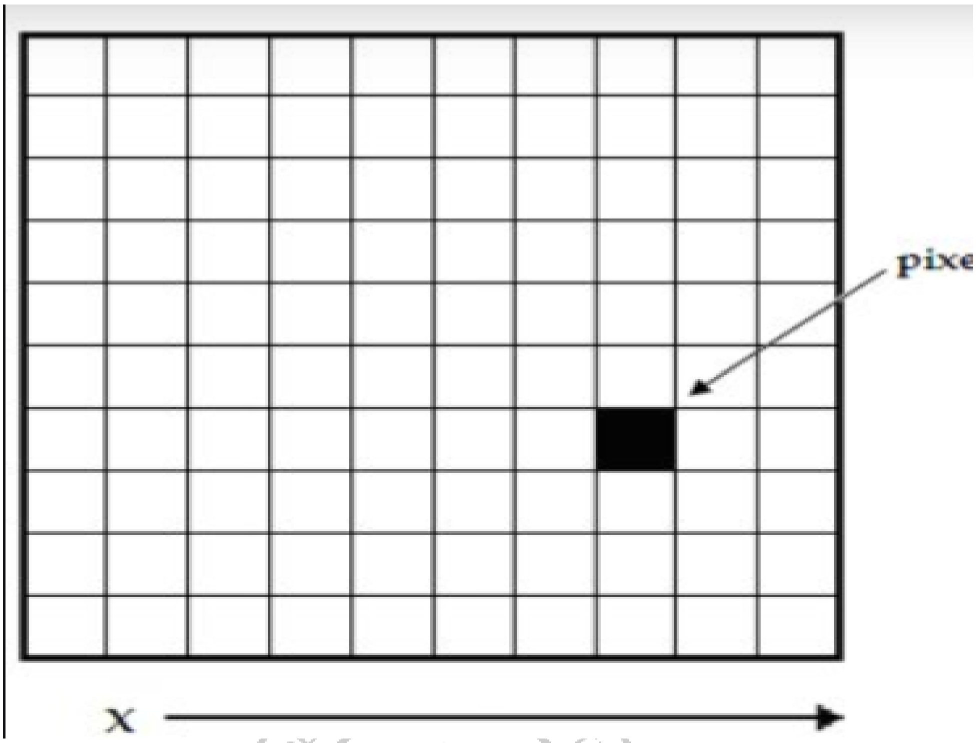

Fig 6.3: 2D Matrix function F(x,y)

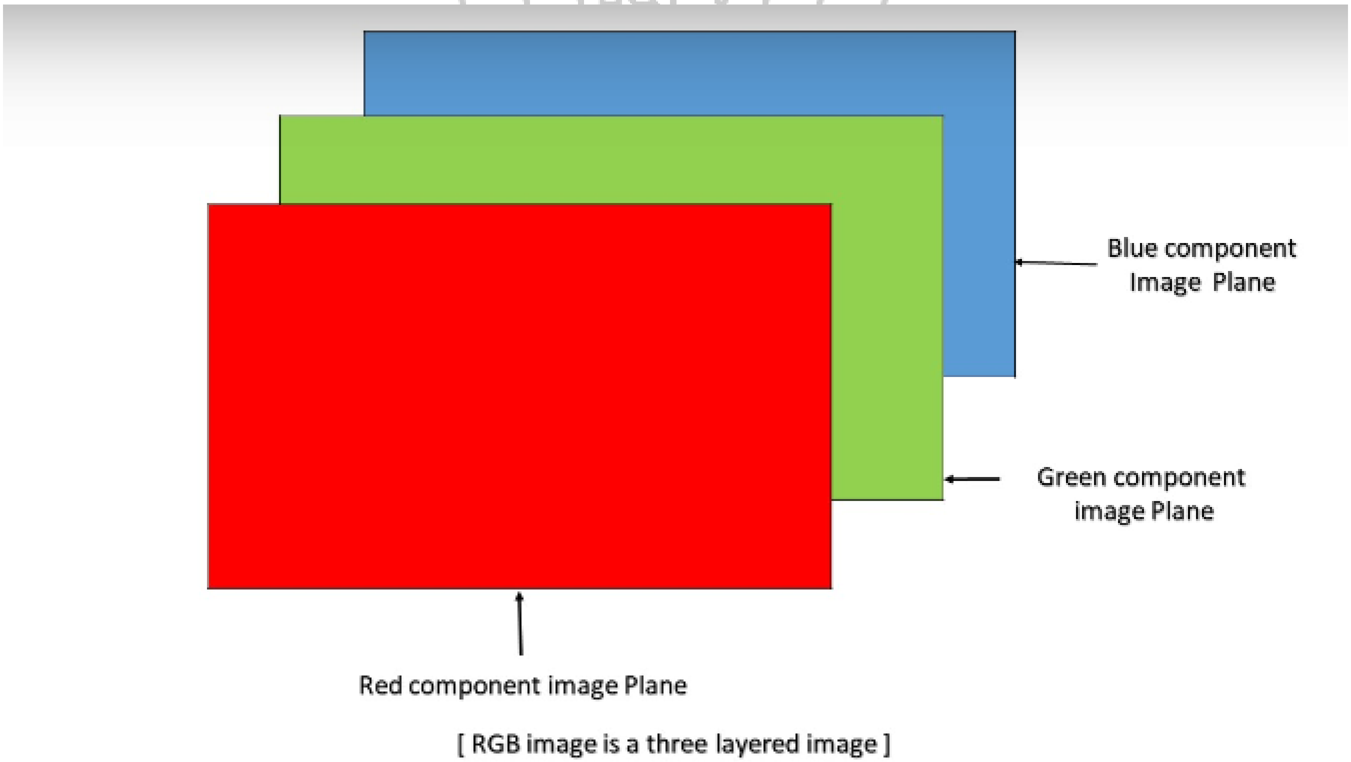

Fig 6.4: RGB Iamge

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CONCLUSION AND FUTURE SCOPE

In this project, we developed a color detection system for color blind individuals using the Manhattan Distance algorithm. The implementation of the system was carried out without relying on built-in functions, emphasizing a logical understanding of this distance metric. While the primary focus was not solely on achieving high accuracy, which could be enhanced through the utilization of built-in functions, the project aimed to provide insights into the performance and computational efficiency of the algorithm on a dataset spanning various color scenarios.

By leveraging machine learning techniques, this project contributes to strengthening proactive measures for aiding color blind individuals in color perception. It enhances our capacity to accurately classify colors and assist individuals in distinguishing between different color categories. This enables stakeholders to make informed decisions regarding color-based tasks and interactions, thereby promoting inclusivity and accessibility in various domains.

Furthermore, the interpretability of the Manhattan Distance algorithm allows for transparent decision-making processes, fostering stakeholder trust in the color detection system. By providing clear insights into color classification decisions, the system facilitates user understanding and acceptance.

While the project has yielded promising results, there remains ample room for further enhancement and exploration. One crucial avenue for future research involves refining the implementation of the Manhattan Distance algorithm to improve its accuracy and efficiency. By optimizing the algorithm's computations and exploring advanced techniques, such as feature selection and ensemble learning, we can potentially enhance the system's color detection capabilities.

Additionally, incorporating domain-specific knowledge and extending the analysis to include real-time data streams could further enhance the system's applicability in real-world color perception scenarios. By considering temporal and spatial features, the system could provide more accurate and contextually relevant color identifications, thereby improving the user experience for color blind individuals.

By advancing proactive measures for assisting color blind individuals in color perception through the application of machine learning techniques, this project contributes to improving accessibility and inclusivity in visual experiences.

CHAPTER-8

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