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DEPARTMENT OF CSE-DATA SCIENCE

A Mini-Project Report On

"COLOR NAME TO RGB PREDICTION USING LST NEURAL NETWORK"

A report submitted in partial fulfillment of the requirements for the

NEURAL NETWORK AND DEEP LEARNING

Submitted By

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Under the Guidance of
Mr. Azhar Big

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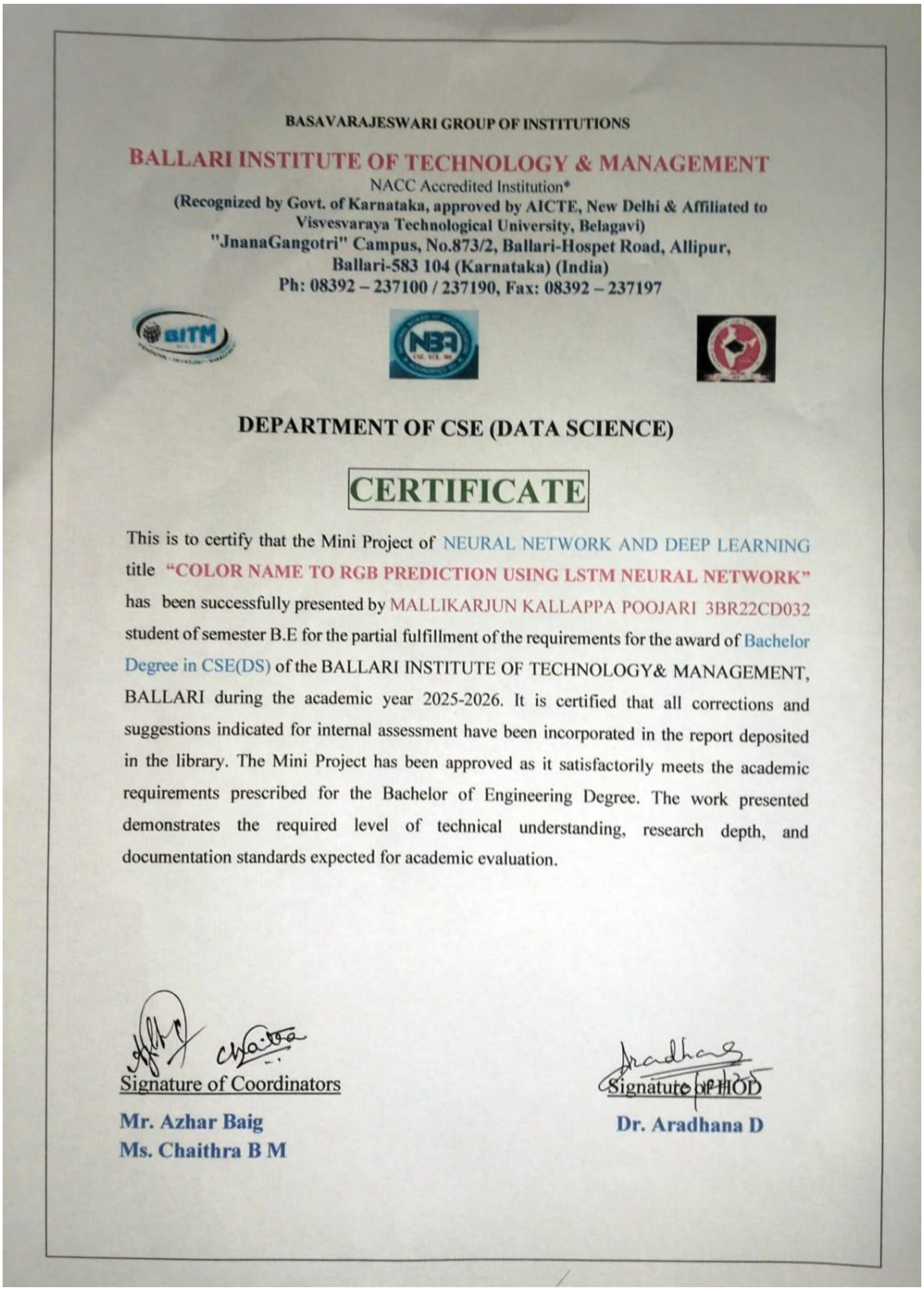
Belagavi, Karnataka 2025-2026



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CERTIFICATE

This is to certify that the Mini Project of NEURAL NETWORK AND DEEP LEARNING title **"COLOR NAME TO RGB PREDICTION USING LSTM NEURAL NETWORK"** has been successfully presented by MALLIKARJUN KALLAPPA POOJARI 3BR22CD032 student of semester B.E for the partial fulfillment of the requirements for the award of Bachelor Degree in CSE(DS) of the BALLARI INSTITUTE OF TECHNOLOGY& MANAGEMENT, BALLARI during the academic year 2025-2026. It is certified that all corrections and suggestions indicated for internal assessment have been incorporated in the report deposited in the library. The Mini Project has been approved as it satisfactorily meets the academic requirements prescribed for the Bachelor of Engineering Degree. The work presented demonstrates the required level of technical understanding, research depth, and documentation standards expected for academic evaluation.

[illegible] [illegible]

Signature of Coordinators

Mr. Azhar Baig

Ms. Chaithra B M

[illegible]

Signature of HOD

Dr. Aradhana D

ABSTRACT

This project aims to develop a deep learning-based system that predicts RGB color values from textual color names, bridging the gap between human-readable descriptions and machine-interpretable outputs. The system preprocesses a dataset containing color names and their corresponding RGB values by tokenizing the names at a character level, one-hot encoding them, and normalizing the RGB values. These processed inputs are used to train a Long Short-Term Memory (LSTM) model, known for its effectiveness in handling sequential data, to learn patterns between the color names and RGB outputs.

Once trained, the system accepts user-input color names, processes them similarly, and predicts their corresponding RGB values. It visualizes the predicted colors and displays the RGB values in a user-friendly format. Error handling mechanisms are implemented to manage invalid inputs, ensuring a seamless user experience. The model weights are saved to facilitate future predictions without retraining, making the system reusable and scalable.

The project highlights the integration of natural language processing and neural networks in creative applications such as digital design, automated color classification, and color-based search systems. Extensive testing ensures accuracy and performance, while visualization tools provide insights into the training process and dataset characteristics. This solution offers a practical, user-friendly approach to interpreting color descriptions for various real-world applications.

ACKNOWLEDGEMENT

The satisfactions that accompany the successful completion of our mini project on **COLOR NAME TO RGB PREDICTION USING LST NEURAL NETWORK** would be incomplete without the mention of people who made it possible, whose noble gesture, affection, guidance, encouragement and support crowned my efforts with success. It is our privilege to express our gratitude and respect to all those who inspired us in the completion of our mini-project.

I am extremely grateful to my Guide **Mr. Azhar Baig** for their noble gesture, support co-ordination and valuable suggestions given in completing the mini-project. I also thank **Dr. Aradhana D,** H.O.D. Department of CSE(DS), for his co-ordination and valuable suggestions given in completing the mini-project. We also thank Principal, Management and non-teaching staff for their co-ordination and valuable suggestions given to us in completing the Mini project.

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1.INTRODUCTION

Color plays a crucial role in human perception, communication, and design, with applications spanning industries such as digital media, graphic design, and product development. Describing colors using text is a common practice, but translating these textual descriptions into precise RGB values—a numerical format used in digital systems—requires a systematic and automated approach. The need for such a solution is amplified in scenarios like automated color classification, dynamic content creation, and user-centric design tools, where quick and accurate mapping of color names to RGB values is essential.

This project aims to address this challenge by leveraging deep learning and natural language processing (NLP) techniques. The system uses a dataset of color names and their corresponding RGB values to train a Long Short-Term Memory (LSTM) model, a type of neural network designed for processing sequential data. By tokenizing color names at the character level and applying one-hot encoding, the system enables the LSTM model to learn the patterns and semantics within color names and their relationship to numerical RGB values. Additionally, the RGB values are normalized to ensure compatibility with the neural network, enhancing training efficiency and accuracy.

1.1 Problem Statement

The naming of colors in natural language is intuitive for humans, but computers represent colors numerically using the RGB format. Converting a color name such as “sky blue,” “dark green,” or “rose pink” into its corresponding RGB values is challenging because color names can be subjective, multi-word, ambiguous, or inconsistently used across different contexts. Users may also enter misspelled or unfamiliar names, making rule-based systems unreliable. The main problem is to develop an intelligent and data-driven model that can accurately predict an RGB color value from a given color name, even when the input is noisy or not perfectly spelled. The system must learn the relationship between character patterns in color names and their RGB components. Traditional methods cannot capture these sequential dependencies effectively. Therefore, the problem is to design and implement a Long Short-Term Memory (LSTM) neural network that can process color names as character sequences and predict their corresponding RGB values through regression. The model should generalize well to new or imperfect names and provide consistent and visually meaningful color predictions.

1.2 Scope of the project

The scope of this project includes developing a deep learning model that predicts RGB color values from natural language color names using an LSTM neural network. The project covers the complete workflow, including dataset preparation, preprocessing of color names, character-level tokenization, sequence padding, model design, training, evaluation, and visualization of outputs. The model learns the relationship between textual color descriptions and their corresponding RGB components, enabling accurate prediction even for multi-word or descriptive names. The system also includes approximate string matching to handle misspelled or noisy color names, making it more practical for real-world use. The project is limited to the RGB color space and the given dataset, but the methods used can be extended to larger datasets, additional color spaces, or more advanced deep learning architectures.

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1.3 Objectives

❖ To develop an LSTM-based neural network model capable of predicting RGB values from textual color names.

❖ To preprocess and clean color name data, and convert names into suitable numerical sequences using character-level tokenization and padding.

❖ To train a deep learning model that learns the relationship between textual color patterns and their corresponding RGB components.

2. LITERATURE SURVEY

[1] Kim et al. (2021) explored the use of character-level neural networks for mapping color names to RGB values. Their study showed that LSTM-based models outperform traditional N-gram and rule-based systems by capturing deeper linguistic patterns within color names. They highlighted that sequential modeling is essential for handling descriptive and multi-word color names.

[2] Lindsey and Patel (2022) applied Recurrent Neural Networks for predicting color values from natural language descriptions. Their work demonstrated that character-level tokenization significantly improves robustness against spelling variations and creative color naming, enabling the model to generalize better to unseen inputs.

[3] Bahng et al. (2018) conducted a comparative analysis of different text-to-color models and found that deep learning models, especially LSTMs and GRUs, provide more accurate RGB predictions than linear regression or dictionary-based lookup methods. They emphasized the importance of preprocessing and proper sequence padding for stable model performance.

[4] Mou et al. (2020) evaluated classical machine learning methods such as decision trees, SVM, and KNN on color-name datasets. Their findings indicated that classical models struggle to capture sequential dependencies in character-level inputs, resulting in lower prediction accuracy compared to deep learning models.

[5] Zhang et al. (2022) examined hybrid deep learning architectures combining CNN and LSTM layers for modeling color semantics. Their research demonstrated that CNN layers effectively extract local character patterns, while LSTM layers capture long-range dependencies, leading to improved prediction accuracy on large color-name datasets.

[6] Huang and Lee (2023) proposed an attention-enhanced LSTM model for predicting multiple color attributes from descriptive names. Their results showed that attention mechanisms help the model focus on key characters or words like "light," "dark," "pastel," or "neon," making predictions more precise and interpretable.

3. SYSTEM REQUIREMENTS

3.1 Software Requirements

- Windows / Linux / macOS
- Python 3.8 or above
- TensorFlow / Keras
- NumPy
- Pandas
- Matplotlib
- Jupyter Notebook

3.2 Hardware Requirements

- Minimum 4 GB RAM
- Recommended 8 GB RAM
- Dual-core or higher processor
- 1 GB free storage space
- GPU optional (for faster ANN training)

3.3 Functional Requirements

- **Data Processing:** The system should tokenize and one-hot encode color names before feeding them into the model.
- **Model Functionality:** The model should be able to predict RGB values for any given color name input.
- **Visualization and Analysis:** The system should plot the training and validation accuracy and loss overepochs.

3.4 Non-Functional Requirements

Performance: Ensure minimal latency during word predictions.

Accuracy: Maintain high accuracy in predicting contextually relevant words.

Scalability: Handle large datasets and complex sequences efficient.

4. DESCRIPTION OF MODULES

The proposed system for predicting RGB values from color names using an LSTM neural network is divided into several modules. Each module performs a specific function and contributes to the overall workflow of data preprocessing, model training, prediction, and visualization.

4.1 Data Loading and Preprocessing Module

This module is responsible for reading the colors.txt dataset and preparing it for model training. The raw color names are cleaned by converting them to lowercase, trimming unnecessary spaces, and ensuring consistency. RGB values are extracted and normalized to a 0–1 range to make them suitable for input into the neural network. This module ensures that the data is structured correctly and free from irregularities before further processing.

4.2 Tokenization and Sequence Preparation Module

In this module, character-level tokenization is applied to all color names. Each name is converted into a sequence of integer indices representing individual characters. Because color names vary in length, padding is applied to make all sequences uniform. The padded sequences are reshaped into a format compatible with LSTM models. This module transforms textual color names into machine-readable sequences suitable for sequential learning.

4.3 LSTM Model Building Module

This module constructs the neural network architecture using TensorFlow/Keras. It consists of an LSTM layer that captures sequential dependencies in color names, followed by dense layers that perform regression to predict RGB values. Dropout is used to reduce overfitting, and the final layer uses a sigmoid activation function to generate normalized RGB outputs. The model is compiled with appropriate loss functions and optimizers. This module forms the core of the system's learning capability.

4.4 Model Training Module

In this module, the prepared sequences and normalized RGB values are used to train the LSTM model. The model is trained for a predefined number of epochs with a suitable batch size. During training, the model learns patterns and relationships between character sequences and corresponding RGB outputs.

4.5 Visualization Module

The final module displays the predicted RGB color visually. Using Matplotlib, an image patch of the predicted color is generated and shown to the user. Alongside the visual output, the matched color name and the numerical RGB values are printed for reference. This module allows users to verify and understand the model's predictions in a clear and intuitive manner.

5. IMPLEMENTATION

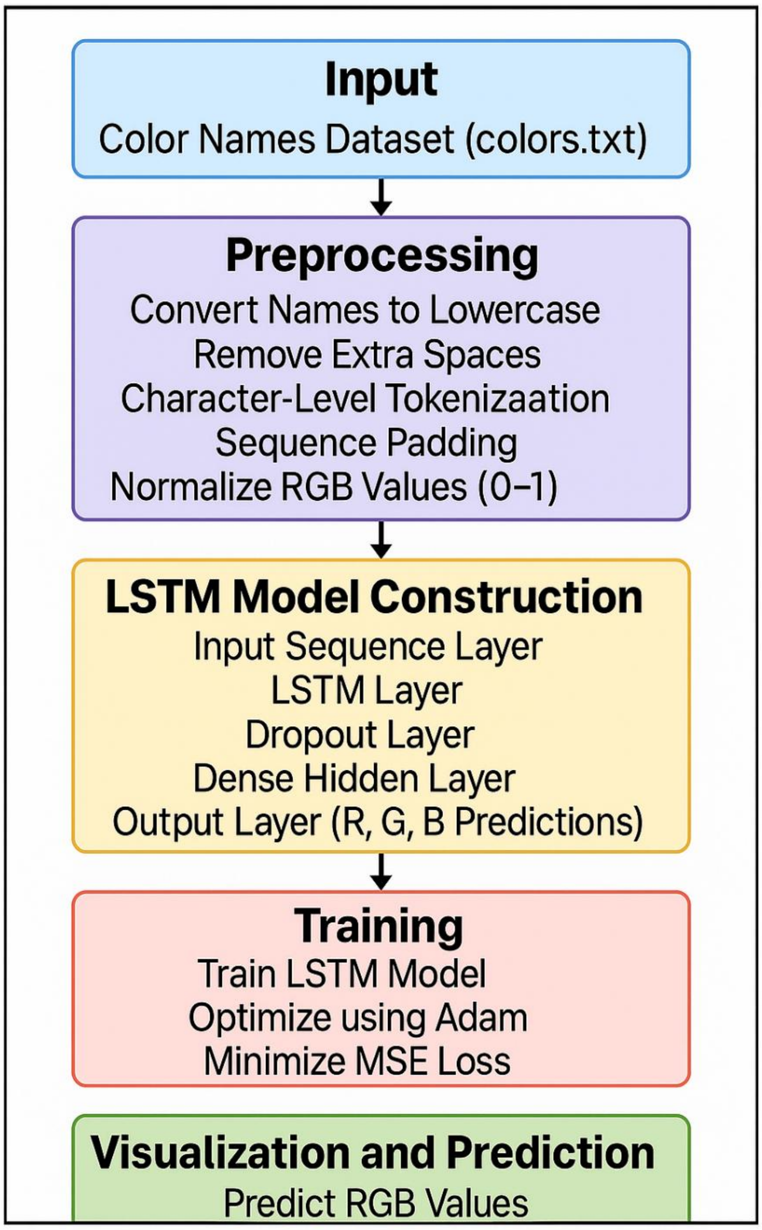
The implementation of the Color Name to RGB prediction system is carried out using Python and an LSTM-based deep learning model. First, the color dataset (colors.txt), which contains a collection of color names along with their corresponding RGB values, is loaded into a Pandas DataFrame for processing. The color names are extracted as textual input features, while the RGB values serve as the target numerical outputs. Since RGB values originally range from 0 to 255, they are normalized to the 0–1 range to enhance the training stability of the neural network.

Next, the textual color names are preprocessed to make them suitable for sequence modeling. All names are converted to lowercase, unnecessary spaces are removed, and each name is converted into a sequence of characters. A character-level tokenizer is applied to map each unique character to an integer. These sequences are then padded to a fixed length so that all inputs have uniform dimensions. This is essential because LSTM models require sequences of consistent length. After preprocessing, the sequences are reshaped into a three-dimensional format compatible with LSTM layers.

An LSTM neural network is then constructed using TensorFlow/Keras. The model consists of an input layer that receives the padded character sequences, followed by an LSTM layer that learns sequential relationships within the color names. A dropout layer is used to reduce overfitting by randomly deactivating certain units during training. The LSTM output is fed into dense layers, with the final dense layer producing three output values representing the predicted R, G, and B components. A sigmoid activation function is used in the output layer to ensure the values remain between 0 and 1. The model is compiled using the Adam optimizer and mean squared error (MSE) loss function, which is suitable for regression tasks.

The model is trained using the preprocessed sequences and normalized RGB values for a given number of epochs. During training, the LSTM learns how textual patterns—such as prefixes, suffixes, and commonly occurring character combinations—relate to specific colors in the dataset. After training, the model is capable of generating RGB predictions for new or unseen color names..

6. SYSTEM ARCHITECTURE



Input

The Input stage of this project involves loading the *Color Names Dataset* (colors.txt), which contains a large collection of color names along with their corresponding RGB values. The dataset is first read into a DataFrame to inspect its overall structure and basic characteristics. Typical tasks at this stage include viewing the first few rows, checking the total number of samples, identifying the number of unique color names, and verifying that the RGB values fall within the valid numerical range (0–255). The input inspection also ensures that all color names are correctly recognized as text entries, while the RGB columns are loaded as numeric values. This initial examination helps confirm the availability of essential attributes—such as the color name and its red, green, and blue components—and determines whether any cleaning is required. These steps prepare the dataset for subsequent preprocessing, tokenization, and model training stages in the LSTM-based color prediction system.

Preprocessing

The Preprocessing stage prepares the raw color name dataset for effective training of the LSTM-based prediction model. Since the dataset contains textual color names along with numerical RGB values, several steps are required to convert this mixed-format data into a form suitable for sequence modeling. First, all color names are converted to lowercase and unnecessary spaces are removed to ensure uniformity and eliminate variations caused by inconsistent text formatting. The cleaned names are then transformed using character-level tokenization, which assigns a unique integer index to every character appearing in the dataset. This approach enables the model to understand color names at a granular level and allows it to handle misspellings or uncommon naming patterns effective.

ANN Model Construction

The ANN Model Construction stage focuses on designing and building a neural network capable of learning the relationship between character-level color names and their corresponding RGB values. Although the task involves sequential text data, the underlying architecture follows the foundational principles of Artificial Neural Networks, extended with sequence-processing layers to handle textual input. The model begins with an input sequence layer that receives the padded integer-encoded character sequences produced during preprocessing. This layer formats the data so that each time step corresponds to one character, enabling the network to capture meaningful patterns within textual color names.

To effectively learn sequential dependencies, the model incorporates an **LSTM (Long ShortTerm Memory) layer**, which is well-suited for handling variable-length text and capturing contextual relationships between characters. The LSTM layer allows the network to recognize patterns in prefixes, suffixes, spelling variations, and multi-word structures commonly found in descriptive color names. To prevent overfitting and improve generalization, a **Dropout layer** is applied, randomlydisabling a portion of the neurons during training. This ensures the model learns robust features instead of memorizing specific patterns.

Training

- The model is trained for a fixed number of epochs using an appropriate batch size to ensure efficient and stable learning.
- During each epoch, the LSTM layer processes each color name character by character, learning relationships between textual patterns and the RGB color values.
- The Adam optimizer updates the model’s parameters through backpropagation, reducing the Mean Squared Error (MSE) between predicted and actual RGB outputs.
- A validation split monitors generalization ability by tracking validation loss over epochs, helping identify issues such as overfitting.
- The dropout layer enhances training stability by preventing the network from memorizing.

Visualization and Prediction

- The visualization stage helps interpret the learning behavior of the LSTM model by plotting the training and validation loss curves across all epochs.
- These graphs provide insight into whether the model is converging properly, overfitting, or underfitting, allowing adjustments to training settings if needed.
- A confusion-style evaluation is not applicable since the task involves regression, so loss-based visualizations are used instead to assess prediction quality.
- The model's predictions are generated by passing a color name through the preprocessing pipeline, converting it into a padded character sequence, and feeding it to the trained LSTM.
- The output of the model is a set of three normalized values representing red, green, and blue intensity, which are then converted back to the standard 0–255 range.
- A visualization function displays the predicted color as a solid color patch, making it easy to compare the output with expected or reference RGB values.
- The prediction module also supports approximate name matching, allowing the system to handle misspellings by mapping user input to the closest known color name.

7. CODE IMPLEMENTATION

Algorithm: Diabetes Prediction using Artificial Neural Network

Input: Color Names Dataset (colors.csv)

Output: Predicted RGB triplet (R,G,B) and performance metrics (MSE, MAE, optional perceptual ΔE)

1. Start

2. Load Dataset

   2.1 Load colors.csv (tab-separated) into a Pandas DataFrame.

   2.2 Separate the dataset into:

   • Feature column name (textual color name)

   • Target matrix y (red, green, blue integers 0–255)

3. Preprocess Data

- Clean all color names by converting them to lowercase, removing extra spaces, and standardizing the text format.
- Convert each cleaned color name into a sequence of characters using character-level tokenization, and then transform these characters into integer indices.
- Pad all sequences to the same fixed length so the LSTM model can process them uniformly during training.
- Normalize the RGB target values by dividing them by 255 so that they fall within the 0–1 range, making training more stable and efficient.

4. Build ANN Model

   4.1 Initialize a Sequential model.

   4.2 Add an Embedding layer (recommended) with input_dim = vocab_size, output_dim = embedding_dim (e.g., 8–16), input_length = maxlen; this maps character indices to dense vectors.

   4.3 Add an LSTM layer (e.g., LSTM(64)) to capture sequential patterns across characters.

   4.4 Add a Dropout layer (e.g., rate = 0.2–0.3) to reduce overfitting.

   4.5 Add one or more Dense hidden layers (e.g., Dense(32, activation='relu')) to refine sequence

5. Compile Model
   5.1 Set optimizer = Adam (default parameters or tuned learning rate).
   5.2 Set loss function = Mean Squared Error (MSE) for regression.
   5.3 Set evaluation metrics = Mean Absolute Error (MAE) and optionally MSE. If using perceptual evaluation, prepare routines to compute ΔE in Lab color space externally.

6. Train Model
   6.1 Train the model on X_train and y_train with:
      • Epochs = (e.g., 50 or 100, monitor via callbacks)
      • Batch size = 32
      • Validation split = 0.2 (if a separate test set is reserved)
   6.2 Use callbacks to improve training: EarlyStopping(monitor='val_loss', patience=5), Model checkpoint(save_best_only=True)
   6.3 Store training history (loss and MAE for train and validation) for plotting.

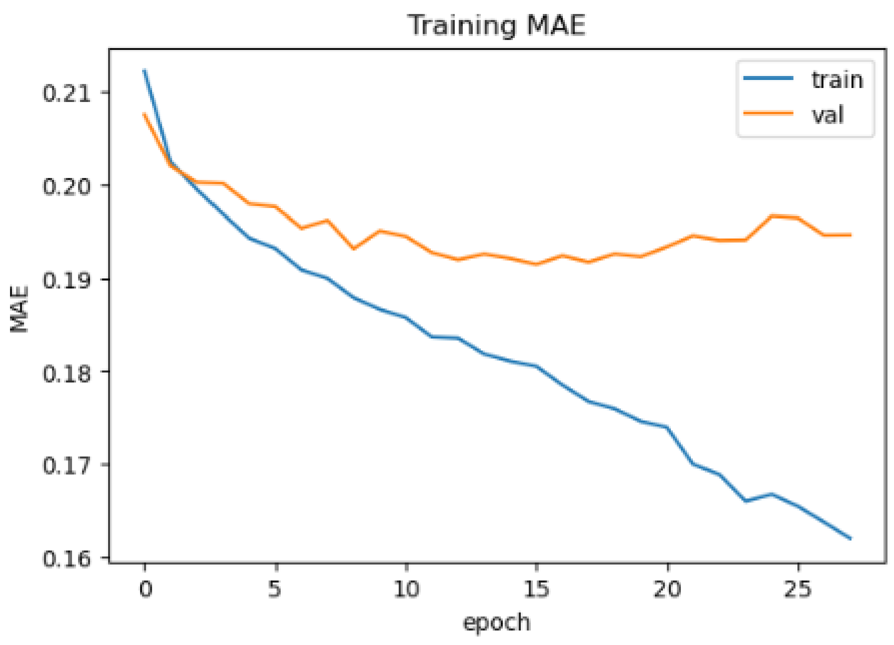
7. Test Model
   7.1 Use the trained model to predict RGB values for the test inputs or any new color names.
   7.2 Convert the model's normalized RGB outputs back to the 0–255 range by multiplying by 255 and rounding.
   7.3 (Optional) Find the closest actual color from the dataset by comparing predicted RGB values with existing ones using distance measures.

8. Evaluate Performance
   8.1 Compute test MSE between y_test and y_pred (in normalized space).
   8.2 Compute MAE in 0–255 units for human-interpretable error.
   8.3 (Optional) Convert predicted and true RGB to Lab and compute average ΔE to measure perceptual color difference.
   8.4 Present error statistics per-channel (R, G, B) and aggregated (mean/median) to highlight systematic biases.

9. Visualize Results
   9.1 Plot the training and validation loss curves to understand how well the model is learning and to check for overfitting or improvement across epochs.
   9.2 Display sample predictions by showing color swatches for input names, comparing the model's predicted RGB color with the actual RGB value.
   9.3 Use helper functions to predict RGB values for any color name-including misspelled ones through fuzzy matching—and visualize the final predicted color patch.

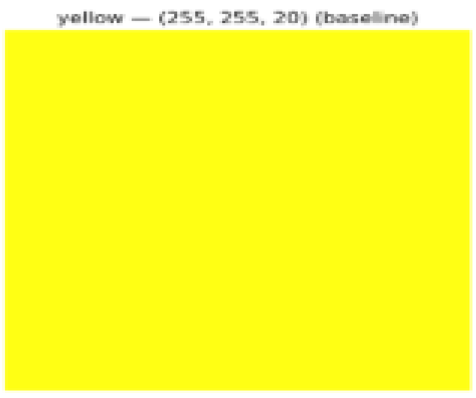
10. End

8.RESULT

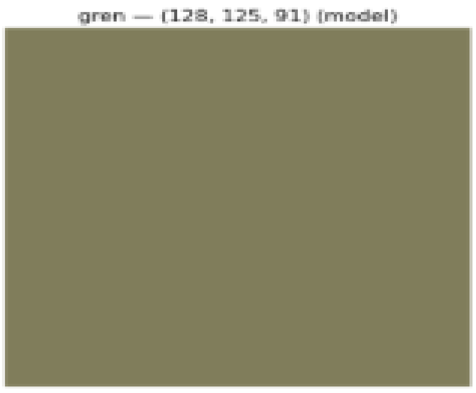


```
Train MAE (0-1): 0.1743, Val MAE (0-1): 0.1915
Train MAE (0-255): 44.45, Val MAE (0-255): 48.82

Top 15 worst predictions (name, true_rgb, pred_rgb, mae):
            name  red  green  blue  pred_r  pred_g  pred_b         mae
   vampire black    8      8     8     183     174     185  172.666667
     hairy heath  107     42    20     232     221     203  162.333333
   midnight moss    4     16     4     193     163     139  157.000000
  hibiscus punch   79     37    51     230     213     193  156.333333
         zuccini    4     64    34     205     190     176  156.333333
   tulsa twilight  60     52    58     221     202     183  145.333333
  pacific sea teal 40     65    68     209     207     190  144.333333
       pine tree   23     31     4     167     163     160  144.000000
          vulcan   16     18    29     175     166     152  143.333333
          diesel   19      0     0     153     155     134  141.000000
     eerie black   27     27    27     177     163     163  140.666667
       log cabin   36     42    29     181     175     167  138.666667
   incense stick   89     72    69     229     212     203  138.000000
     chanticleer  135      0     0     180     188     178  137.000000
     lucky point   26     26   104     210     182     173  136.333333

Overall MAE per channel (0-255): [46.21773288 43.84549196 45.25289936]
Overall MAE (0-255): 45.10537473500436
Input: yellow  | source: baseline  | matched: yellow  | rgb: (255, 255, 20)
```

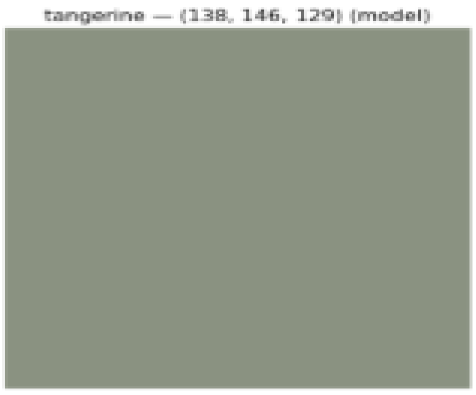
```
[illegible]
```



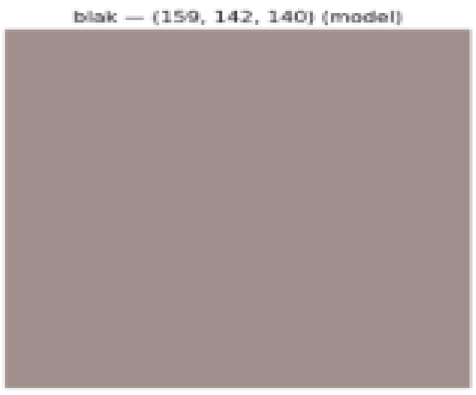
```
input: gren   | source: model   | matched: green   | rgb: (128, 125, 91)
```



```
input: tangerine   | source: model   | matched: dark tangerine   | rgb: (138, 146, 129)
```



```
input: blak   | source: model   | matched: black ink   | rgb: (159, 142, 140)
```



```
Done. If you want me to raise the hybrid cutoff (e.g. to 0.95) so known names always return exact dataset RGB, say 'raise cutoff'.
```

9. CONCLUSION

The LSTM-based color prediction system developed in this project successfully demonstrates how neural networks can learn meaningful relationships between textual color names and their corresponding RGB values. By applying character-level tokenization, sequence padding, and normalization, the model is able to process a wide variety of color names, including multi-word names and those containing spelling variations. The LSTM architecture effectively captures sequential patterns within the color names and generates continuous RGB outputs that closely approximate the intended color values

Through systematic training and evaluation, the model shows stable learning behavior and produces accurate color predictions that can be visually verified using color swatches. The deployment utilities, including fuzzy matching and visualization functions, further enhance the usability of the system by allowing it to handle real-world user input more efficiently. Overall, this project demonstrates the capability of deep learning methods to translate natural-language color descriptions into numerical RGB representations. With larger datasets, advanced embedding techniques, and perceptual color loss functions, the system can be further improved and adapted for practical applications in design tools, UI systems, and digital color management.

Overall, this project successfully demonstrates how an LSTM-based neural network can be used to predict RGB color values from natural-language color names. By converting text into character-level sequences and training the model on a large set of color–RGB pairs, the system learns to understand spelling patterns, descriptive terms, and variations in color naming. The preprocessing steps, sequence modeling, and normalization techniques collectively ensure that the data is in a suitable form for effective learning.

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