Research Article

# TEXTILE DYEING PROCESS AND DYEING RECIPE PREDICTION USING ARTIFICAL INTELLIGENCE

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## ABSTRACT

In this study, a comprehensive analysis is presented of the determination and estimation of the sample color or target color taken from the customer in the laboratory department of textile dyeing companies. The importance of the textile industry in the world and in Turkey is also mentioned. In the report published by Statista, it is seen that the textile industry has a share of 3.3% in Turkey and the world. In this work, a sample study was conducted in a textile finishing company, and the processes were shared. First, the classical processes used to determine the target color are explained in detail. Then, it was mentioned how the data obtained with the spectrophotometer device is used in color estimation using machine learning methods and artificial neural networks. According to the results of the examination, it is seen that the data obtained with the hyperspectral camera device is estimated by the long-short-term memory (LSTM) model since the spectrophotometer device is expensive and has not given accurate results recently. In addition, it has been observed that this model gives better results than the same model created from the data obtained with the spectrophotometer device.

**Keywords:** Dyeing Recipe Prediction, Artificial Intelligence, Textile Dyehouse, Color Space, Spectrophotometer

# TEKSTİL BOYAMA SÜRECİ VE YAPAY ZEKA KULLANARAK BOYAMA REÇETESİ TAHMİNİ

## ÖZET

Bu çalışmada tekstil boyama firmalarının laboratuvar bölümünde müşteriden alınan numune renginin veya hedef rengin belirlenmesi ve tahmin edilmesi üzerine kapsamlı bir analiz sunulmaktadır. Tekstil sektörünün dünyadaki ve Türkiye'deki önemine de değinilmektedir. Statista'nın yayınladığı raporda tekstil sektörünün Türkiye'de ve dünyada %3,3'lük bir paya sahip olduğu görülmektedir. Bu çalışmada bir tekstil terbiye firmasında örnek bir çalışma yapılmış ve süreçler paylaşılmıştır. İlk olarak hedef rengi belirlemek için kullanılan klasik süreçler kapsamlı bir şekilde anlatılmıştır. Ardından spektrofotometre cihazı ile alınan verilerin makine öğrenmesi yöntemleri ve yapay sinir ağları kullanılarak renk tahmininde nasıl kullanıldığından bahsedilmiştir. Yapılan inceleme sonuçlarına göre son zamanlarda spektrofotometre cihazının pahalı olması ve kesin sonuç vermemesi sebebiyle hiperspektral kamera cihazı ile elde edilen verilerin uzun kısa-süreli bellek (Long Short-Term Memory-LSTM) modeli ile tahmin edildiği görülmektedir. Ayrıca bu modelin spektrofotometre cihazı ile elde edilen verilerden oluşturulan aynı modele göre daha iyi sonuçlar verdiği gözlemlenmiştir.

**Anahtar Kelimeler:** Boyama Reçetesi Tahmini, Yapay Zekâ, Tekstil Boyahanesi, Renk Uzayı, Spektrofotometre

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## 1. INTRODUCTION

The term "textiles" refers to the basic materials made from woven fibers, but clothing and other items are created from those materials using other processes, such as stitching. The primary types of textiles include mills that make other textile products, such as fabrics, yarn, and fiber, as well as floor coverings, furniture, and textile and fabric finishing. With a compound annual growth rate (CAGR) of 6.6%, the global textile industry increased from $573.22 billion in 2022 to $610.91 billion in 2023. The possibility of an international economic rebound brought on by the COVID-19 pandemic was, at least temporarily, constrained by the conflict between Russia and Ukraine (Textile Global Market Report, 2023).

Economic sanctions against several nations, an increase in commodity prices, and supply chain disruptions as a result of the conflict between these two nations have raised the price of goods and services and had an impact on numerous international marketplaces. With a CAGR of 5.5%, the global textile market is projected to reach $755.38 billion in 2027 (Textile Global Market Report, 2023).

The need for smart textiles is being driven by improvements in wireless technology and an increase in the demand for connectivity. Smart textiles are materials with an environmental response. They are capable of responding to external physical stimuli from mechanical, electrical, chemical, and thermal sources. The three main parts of smart textiles are sensors, actuators, and fabrics. Metals, conductive polymers, and optical fibers are some of the materials utilized in smart textiles. They are extensively employed in the military, fashion, entertainment, health care, transportation, sports, and physical fitness. One such tool on the Citizen Science d-shirt is a heart rate monitor, along with an integrated GPS, accelerometer, and altimeter. In 2022, Asia-Pacific was the region with the largest textile industry. Western Europe was the second-largest textile market area (Textile Global Market Report, 2023).

Daiwabo Holdings Co. Ltd., Tarkett S.A., Mohawk Industries Inc., Masco Corporation, Toray Industries Inc., Ashley Furniture Industries Inc., Daiwabo Holdings Co. Ltd., Berkshire Hathaway Inc., Far Eastern New Century, Beaulieu International Group, and Grasim Industries Limited are significant players in the textile industry (Textile Global Market Report, 2023).

Fashion is a global industry that has been shown to bring in USD 2.5 trillion each year and employ 75 million people worldwide (Chen et al., 2021).

In a country that has had a long history dating back to the Ottoman Empire, textile manufacturing has remained an integral part of its varied economy. Turkey currently ranks as the fourth-largest exporter of textiles worldwide and is a vital component of an industry that exports more than double what it did in 2000. The Turkish clothing and fabric industry beat out many other countries for this distinguished spot due to its competitive cost, a wide variety of products, and outstanding growth opportunities in retail (Textiles and Clothing Industry in Turkey, 2022).

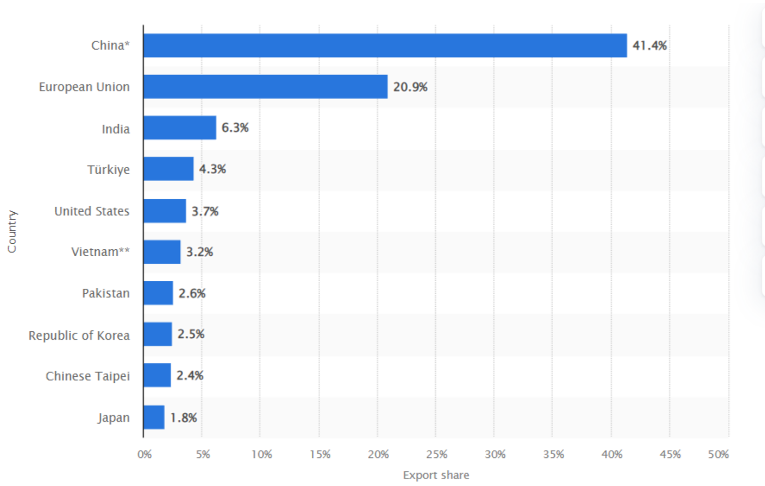



**Figure 1.** Leading textile exporters in 2020, by country.

Figure 1, as seen in Turkey in 2020, shows that in all countries, in the textile industry, 3.3% has a share. Raw materials make up the majority-more than half, actually-of costs in the textile industry, except for those businesses that deal specifically with dyeing and finishing. These raw materials basically consist of cotton fibers and artificial fibers such as nylon or polyester. Labor comes in second place as far as impacting costs are concerned (about

25%). The proportion of raw materials in overall costs declines in dyeing and finishing operations, while energy costs and depreciation take center stage (Uyanik and Celikel, 2019).

**Table 1.** Cost components in the textile industry.

| Share of Main Cost Items (%) | Textile (General) | Textile (Dyehouse) |
|---|---|---|
| Main Material/Chemical Material | 33 | 15 |
| Dyeestuff | 4 | 10 |
| Other Auxiliary Substances | 7 | - |
| Workmanship/Human Resources | 25 | 26 |
| Depreciation | 7 | 17 |
| Energy | 9 | 16 |
| Financing | 3 | 2 |
| Maintenance and repair | 2 | 3 |
| Other expenses | 10 | 11 |

From any given color, one can create an estimated recipe and representative dyes, with results determined by reviews of archives, to determine the estimated recipe that best follows the target color. The target color should be close enough to the archive colors so as to optimize dye creation, giving a truer representation of what that color would look like when creating actual garments. For this reason, it is ideal for the samples used in color tests to also be archived whenever possible and therefore available for future comparisons. It is vital that you consider all your available natural ingredients when developing your recipe, as well as the color depth and nuances of each dye based on its current state. You know, different variations of dye are in different shades, so it’s important to pay attention to your resources while creating a recipe and not simply throw away any ingredient you have because they will all have an impact on the outcome of your finished recipe.

For fashion brands, reproducing your brand’s shades accurately is imperative. Looking at color samples and adhering to the most accurate hues that you can is what will determine whether or not your textile-related documents gain or lose profit. Some printing and dyeing factories still use methods that are human-centric, but those using a new process that instills color into cloth through algorithmic programming are gaining traction, especially among the more important partners and clients of the fashion industry. It is challenging to match the market’s expectations for accuracy, speed, and customization because of these human-centric procedures. In order to increase the effectiveness and accuracy of color matching, computer-aided color matching for textile dyeing and printing is an important research issue. It is also an important way for textile businesses to increase their level of global competitiveness (Chen et al., 2021).

The rest of the paper is organized as follows. Section 2 mentions how a target color is found in a laboratory environment. In Section 3, a practical study conducted with expert knowledge in a laboratory environment in a textile company is introduced. Artificial intelligence in textile industry is mentioned in Section 4 and artificial intelligence methods are examined in Section 5. Section 6 includes the color spaces used in recipe prediction. The spectrophotometer and hyperspectral camera are explained in Section 7. In Section 8, various artificial intelligence models utilized for dyeing recipe prediction are investigated. Finally, conclusions are summarized in Section 9.

## 2. FINDING THE TARGET COLOR

In this section, the selection of dyestuff suitable for the target color will be explained.

### 2.1. Structure and Properties of Textile Fabrics

In the first two sections, the importance of fabric type and the importance of dye selection were mentioned. The method used to create all textile materials begins with fibers, regardless of the variety of physical and structural forms they take or the chemical makeup of the materials from which they are formed. According to textile terms and definitions, a textile fiber is a raw material that is typically characterized by flexibility, fineness, and a high length to thickness ratio. Only around 7% of all fibers are thought to be used directly in the production of final goods; instead, the majority of fibers are thought to be spun into yarns before being transformed into fabrics. Dyeing processes with mixtures of fibers also differ (Grishanov, 2011).

## 2.2. Fabric Dye Selection

The best fabric dye is not as easy to choose as you might believe. Given the vast variety of dyes and materials, this process may prove challenging. It happens that when someone wants to dye fabric for the first time, their first thought is usually, “What color should I use?” However, you should actually start by asking, “What sort of fabric dye do I need?” You must be aware of the type of yarn used in the fabric in order to respond to this query. Each of them will be better suited for a certain type of yarn, while some of them won’t work with all yarn types. It is crucial to select the best dye for the fabric you will be working with, but you should also be aware that some dyes may be more poisonous or harmful to the environment than others (Grishanov, 2011).

## 2.3. Receiving Sample from Customer

A customer takes an existing piece of fabric or a textile sample to a textile dyeing house and asks them to match the color with dye. The dyeing house then takes that piece of cloth to a textile lab, where they build a digital mock-up of the color before approving it. Once approved, the materials in question are sent back to the customer, where they are dyed with dye mix-match.

As can be seen in Figure 2, to know the best shade of a color, one needs to identify the pantone number and confirm the material. The common standard is the Pantone Matching System, which has a unique identifying number for each shade, though there are many other alternatives nowadays.


**Figure 2.** Color pantone.

As can be seen in Figure 3, if a customer wants to request the color of any type of textile, the customer can send representative samples of different colors and ask for an order after choosing and becoming satisfied with his or her chosen colors.

**Figure 3.** Colored textile material.

The colors our customers choose for their specimen are identified by a number when we work at the dyehouse. When ordering the same color again, our customers use this number to ask for it. As can be seen in Figure 4, pre-painted color in this manner, the customer can request on this color.

**Figure 4.** Pre-dyeed customer color.

## 2.4. Creating Estimated Recipe for Target Color

First, a spectrophotometer is used to create an estimated formula for the desired target color, as well as a search for recipes from the archive.

### 2.5. Looking at Archive

Each different recipe is stored in its own special envelopes inside a folder. The folder contains things such as the customer's name, the number of colors used, the type of fabric, the dyeing instructions, and samples of swatches suitable for the final product. As can be seen in Figure 5, for each main colour in the book are kept in the archive.

**Figure 5.** Archival data.

### 2.6. Determination of Recipe by Spectrophotometer

A spectrophotometer is a device for measuring color that receives a color value by measuring the way light interacts with an object. The device also includes filters that allow us to see how much of the spectrum (such as UV, blue, red and yellow). Measurement and evaluation of a number assigned to the color of an object; this procedure is carried out according to international standards. The spectrophotometer has many features:

- Determining a recipe for a new color,
- The process of finding the nearest color from the color archive,
- Calculation of the amount of g/kg of dye according to the production quantity of the found recipe,
- Calculation of the recipe dye price,
- Transfer of the recipe to the color archive (Ministry of National Education, 2011).

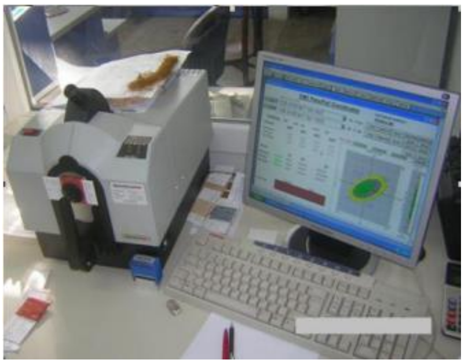


**Figure 6.** Spectrophotometer device.

The following are the color measurement stages of the newly arrived sample with a spectrophotometer.

**Figure 7.** Placing the sample in the appropriate place.

**Figure 8.** Closing the lid so that it does not see the light.

As in Figure 6, the sample is read to the spectrophotometer and displayed on the screen with the desired recipe alternatives. Figures 7 and 8 show how the sample should be placed. Figure 9 shows the images given to the spectrophotometer device for a new dye.

**Figure 9.** Dyeing of colors certain intervals.

The colors of the dyestuffs dyed on the spectrophotometer should be given certain intervals. Because in order to make a recipe estimate, it is necessary to recognize the existing colors. As can be seen from Figure 9, about 15 colors were studied. While there are positive sides to using a spectrophotometer device, there are also negative sides.

A recipe is formulated using dyes selected for this color, taking into consideration the recipes of nearby colors found from our archive for the target color as well as the individual measurements determined by a spectrophotometer. The formulation can then be made in one of multiple ways. When creating a recipe, it is important to have some general knowledge about the colors you might use in that recipe. As you might already know, there are different kinds of dyes that vary in degree of depth and tone – each with their own characteristics and abilities.

One of the negative aspects of the spectrophotometer is that no domestic product has been developed in our country. In addition, with the recent increase in inflation and the impact of the dollar exchange rate, it has become even more difficult to buy a spectrophotometer device. In order to eliminate the dependence on the spectrophotometer device and to present different perspectives in this period when the digital transformation accelerated so much after the pandemic period, this study has been put forward.

## 3. SAMPLE WORK IN THE LABORATORY OF TEXTILE DYEING COMPANY

In this section, the recipe preparation process was applied with expert knowledge in a textile dyeing company. The application is explained with an example. The dyeing process is shown in Figure 10.

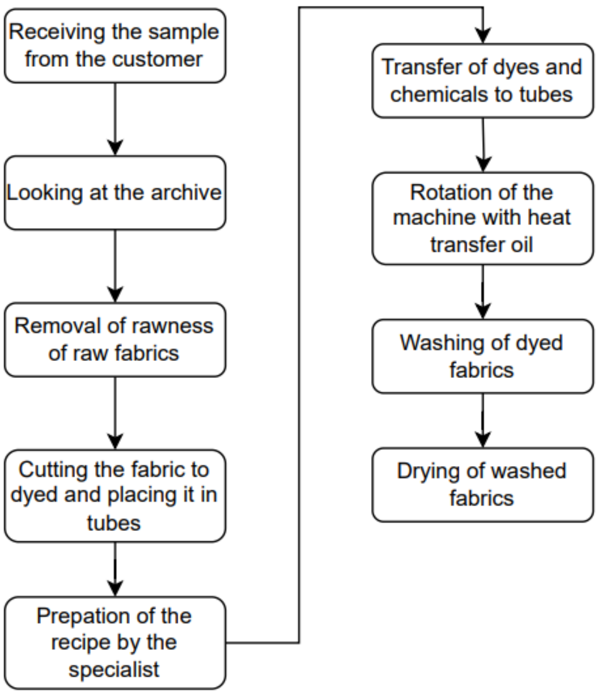



**Figure 10.** The process of dyeing fabrics.

**Figure 11.** Raw fabric from customer.

Before dyeing the fabric in the laboratory, the rawness removal process is applied. With this processing, the raw fabric from the customer loses its properties. The raw fabrics from the customer are shown in Figure 11. As an example, six different cotton fabrics are shown in Figure 12 below.


**Figure 12.** Types of cotton fabrics.

Vegetable oils from the field, mechanical oils from plants or knitting machines, etc. that’s why this process is being done. In short, the pollution in the cotton, yarn, knitting process is discarded before dyeing. This checkout process also varies according to the demands of customers. As an example, it is requested to use depilatory, so that the fabric looks brighter. This process is not performed if the customer's fabric is lint-free because it makes disinformation.

Cotton dyeing was performed in this study. A disbergator is not provided for cotton dyeing. It is provided in polyester fabrics. Water, alkali, and salt are given in cotton dyeing. For fabrics that are both cotton and polyester, polyester is dyed first and then cotton. Polyester fabric is dyed at 130 degrees and cotton fabric is dyed at 70 degrees. Hydro sulfide is also used on cotton when washing polyester. In cotton dyeing, an ion holder is used. One or two drops are placed in the water. The possibility of hard water is resisted. It is not used on polyester.

While creating recipes within the enterprise, recipes are also created with different dye brands other than the same dye brands. When creating a recipe for this, in addition to keeping the color, attention is also paid to the cost.

The stages after the preparation of the recipe are mentioned in an ordered manner below:

- In the enterprise where the sample study was conducted, the fabrics are made in 10 gr. After the fabrics from the customer are weighed, they are soaked with water in a beaker.
- Before the recipe was written, recipes were created by looking at the book of the nearest color and the customer’s other orders through the notebooks in Figure 5 with expert knowledge. After the recipe is written, the dyes will be pipetted. The recipe written by the specialist are shown in Figure 13 below.

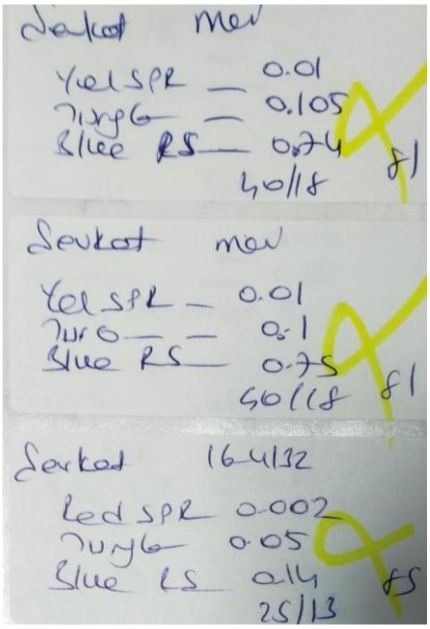
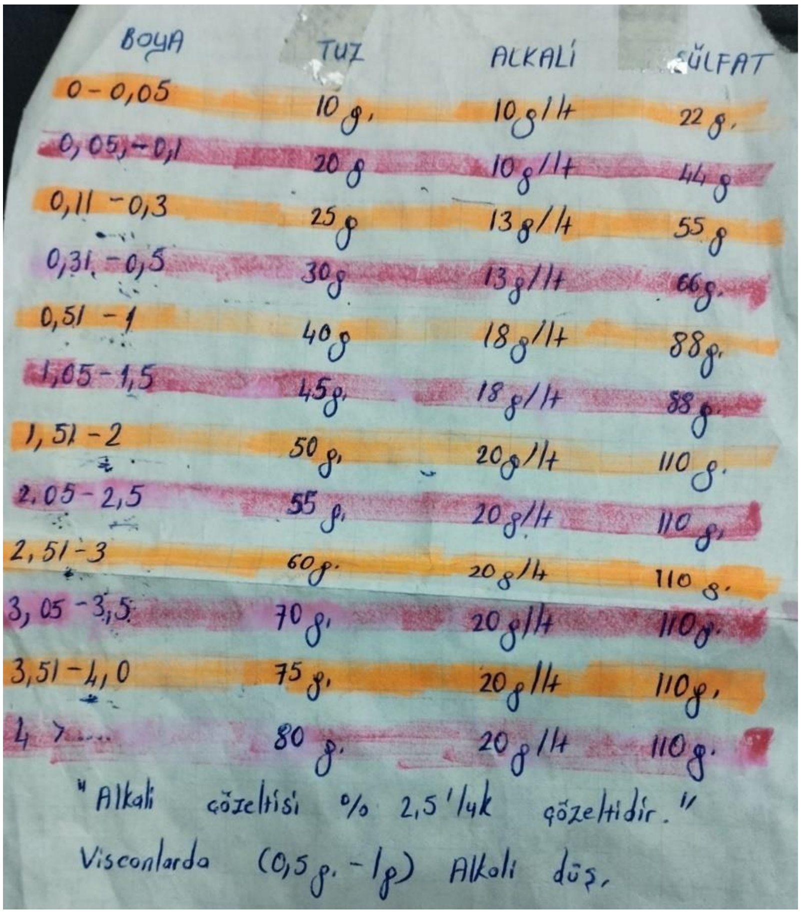


**Figure 13.** Recipe list.

There is a formula for the proportions of salt, soda, alkali, water in the recipe created by an expert. This is also shown in Figure 14.



| BOYA | TUZ | ALKALİ | SÜLFAT |
|---|---|---|---|
| 0 - 0,05 | 10 g. | 10 g/lt | 22 g. |
| 0,05 - 0,1 | 20 g | 10 g/lt | 44 g |
| 0,11 - 0,3 | 25 g | 13 g/lt | 55 g |
| 0,31 - 0,5 | 30 g | 13 g/lt | 66 g. |
| 0,51 - 1 | 40 g | 18 g/lt | 88 g. |
| 1,05 - 1,5 | 45 g. | 18 g/lt | 88 g |
| 1,51 - 2 | 50 g. | 20 g/lt | 110 g. |
| 2.05 - 2,5 | 55 g. | 20 g/lt | 110 g. |
| 2,51 - 3 | 60 g. | 20 g/lt | 110 g. |
| 3,05 - 3,5 | 70 g. | 20 g/lt | 110 g. |
| 3,51 - 4,0 | 75 g. | 20 g/lt | 110 g. |
| 4 > ... | 80 g. | 20 g/lt | 110 g. |

"Alkali çözeltisi % 2,5'luk çözeltidir."

Visconlarda (0,5 g. - 1g) Alkali düş.

**Figure 14.** Salt, alkaline, soda proportions.

The powder state of the dye is shown in Figure 15.

**Figure 15.** Powder color.

10% of the dye is dissolved in 1000% erlens. After weighing 10 g of dye, the dyes are dissolved at 60 degrees. It is dissolved in soft water; it should not be hard water. Water is added to 1000 ml to complete the erlene. As can be seen in Figure 16, a navy blue (Black B crude color was made).

**Figure 16.** Black B crude navy-blue color.

Salt, alkali and soda are added to the tubes at the pipetting stage. Salt should definitely be added because it makes the dye stick. Pipetting was performed with an automatic pipette device. The tube is 100 cc. In Figure 17, the above-mentioned substances are added to more than one tube.

**Figure 17.** Pipetting device and tubes.

Since the dyes and substances added in Figure 18 are processed in more than one tube, the colors are checked on the fabric by the specialist before being taken into the machine.

**Figure 18.** Recipe control.

Soda is used in light colors, while alkali is used in dark colors.

- After the tubes are closed, they are taken into the machines with heat transfer oil. It rotates in the machine for about 2.5 hours.

- After dyeing, the washing process is performed. After the cotton dye rises to 70 degrees, it falls to 30 degrees in the machine. Pickling is performed by adding one or two drops of acetic acid while washing in boiling water. Because the dead dye on it is expected to be discarded. It is washed several times with soap to remove the dead dye.
- After the washing process is completed, the drying process is carried out with a survey machine. It is dried at 150 degrees; this process takes 15 minutes.

This sample study was carried out at the textile dyeing house company in Istanbul. These operations were carried out in the laboratory environment, the color approved by the customer on the laboratory side is carried out in large machines inside the factory. The process for recipe prediction is described with details.

## 4. TEXTILE INDUSTRY, ARTIFICIAL INTELLIGENCE AND DYEING RECIPE PREDICTION

In this section, the methods in the articles examined in the literature study are briefly mentioned. The use of artificial intelligence in the textile sector is also mentioned.

Since the 1980s, computer algorithms and machine learning have aided the bulk of textile testing. The majority of testing and quality control tasks presently using image processing are handled by automation, deep learning, and neural networks (Sikka et al., 2022).

Making machines that think and act like humans is the ultimate goal of artificial intelligence. The artificial neural network (ANN) technique employs back propagation with a programmable learning rate, multiple linear regressions, and multiple linear regressions. It can assist with forecasting yarn quality, identifying fabric issues, rating fibers, and forecasting dye recipes. Its applicability to a wide range of aspects of the textile industry, from raw materials to completed textiles, has sparked a great deal of debate. This study investigates the complete dye synthesis process. ANFIS, an adaptive neuro-fuzzy reasoning system, has recently been employed to assess yarn characteristics. In order to predict useful properties of materials like air permeability, moisture content, and heat transfer rates, the textile industry also uses ANN (Sikka et al., 2022).

In the textile business, coloring or dying has typically been a precise process. The production of dye mixtures, the application of dye to fabric, and the inspection of dyeing all took place before computers and mechanization. Without human assistance, AI has made it possible to find flaws, match hues, and create dependable dyes. In the early 1940s, recipe prediction algorithms used the Kubelka-Munk (KM) model. According to the KM theory, colorants are categorized by their K and S absorption and scattering coefficients (Sikka et al., 2022).

A neural network-based scanner for color matching reactive colored cotton was created by Almodarresi et al. (2013). K-M color matching techniques include colorimetric and spectrophotometric matching. The former is based on Allen's method, which addresses equalization of tristimulus values under specific observational conditions. Using a neural network and scanner rather than a spectrophotometer, reactive dyed cotton sample color formulation can be predicted with more accuracy. Fabric samples were scanned using the scanner at 150, 300, and 600 dpi. A neural network was fed by the histograms of the pictures. Using 15, 30, and 60 input vectors, three output neurons, and a hidden layer with variable numbers of neurons, the input layer trained neural networks. The least mean square error for a neural network with 24 hidden neurons and 60 input vectors from 300 dpi photos was 3.319710-5.

Haji and Vadood (2021)'s polyester clothing was dyed with madder, a natural eco-friendly pigment. The following five variables were used to color 46 samples: dye concentration, dye bath pH, temperature, duration, and liquor ratio. The measured K/S values were predicted using ANN and fuzzy logic models. To increase model precision, the genetic algorithm was applied to both models. The most accurate ANN and fuzzy models could forecast K/S values with mean absolute percentage errors of 2.52 and 3.01, respectively.

An ANN-based system for printing that selects the ideal pigment mixtures were created by Golob et al. (2008). They demonstrated that by using counter propagation neural networks, it is feasible to recognize color or pigment combinations in textile printing. To teach the neural network, they used 1,430 samples of cloth printed with ten different colors.

CMR-color, an automatic color matching prediction model, enhances the capacity to extract high-dimensional characteristics from spectral data by combining three neural network models: the standard, multilayer perceptron (MLP), ResNet and convolutional neural network (CNN) (Chen et al., 2021).

Support vector machine (SVM)-based evaluation model accuracy was projected to be 98.2% (Sikka et al., 2022).

SenthilKumar (2007) proposed a feedforward neural network model using CIELAB values as input. The following findings came from a study on using neural networks to simulate CIELAB values for time dyeing parameters for any vinyl sulfone dye. The neural network built using input and output parameters has L*a*b* values for vinyl sulfone colors.

This research was conducted in order to evaluate the development of new artificial intelligence-based prescription prediction systems for textiles.

## 5. ARTIFICIAL INTELLIGENCE METHODS

In this section, the methods in the studies examined will be briefly mentioned technically.

### 5.1. Multi Layer Perceptron

The MLP model is one of the more appealing conceptual neural network models. This paradigm, in its most basic version, consists of a finite number of succeeding layers. There are a limited number of units in each tier (often called neurons). Each unit in a layer is connected to every other unit in the layer below it and vice versa. Links or synapses are the typical names for these connections. Information is transferred from one layer to the next one (thus the term feedforward). The input is contained in the top layer, which is known as the input layer. Next, there are intermediary layers known as hidden layers. The final layer, aptly referred to as the output layer, yields the final product. Figure 19 shows the structure of MLP (Pinkus, 1999).

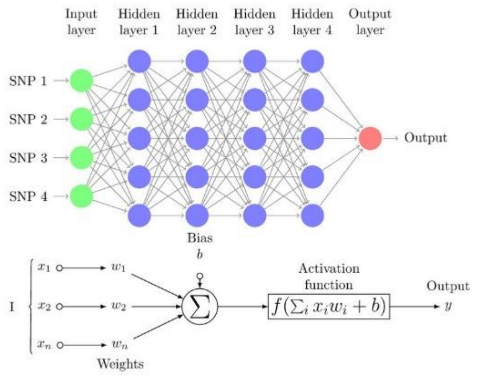



**Figure 19.** MLP structure.

### 5.2. Convolutional Neural Network

The most popular deep learning architecture is the convolutional neural network. It was influenced by the animal visual cortex. Its primary use at first was for object identification tasks, but it is now being researched for use in a wide range of other tasks, such as object tracking, position estimation, visual saliency detection, text detection and scene labeling, action recognition and many others. The 1980 invention of Neocognitron is considered as ConvNets' forerunner. LeNet, a groundbreaking innovation in convolutional neural networks, was developed in 1990 by LeCun et al. and subsequently improved. It was developed mainly to classify handwritten digits and was successful in recognizing visual patterns without any previous image processing (Aloysius and Geetha, 2017).

However, this design was unable to handle complicated issues due to a lack of training data and computational capacity. A CNN model developed by Krizhevsky et al. later in 2012 was successful in lowering the mistake rate in the ILSVRC competition. Their work has since grown to be among the most important in the field of computer vision, and many people use it to experiment with different CNN architectures. Figure 20 shows the structure of CNN (Aloysius and Geetha, 2017).

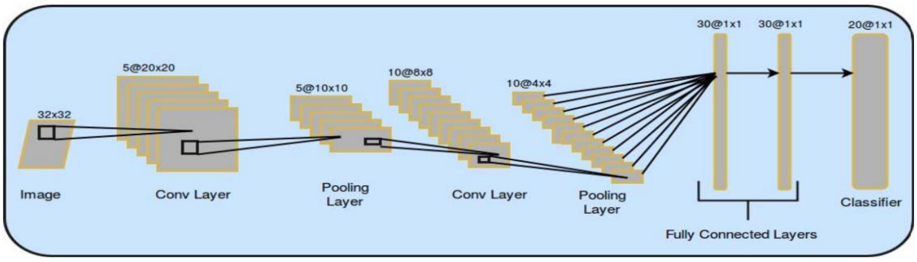



**Figure 20.** CNN structure.

### 5.3. Recurrent Neural Networks and Long Short-Term Memory

Recurrent neural networks (RNNs) are widely used in research areas that use sequential data, audio, including text and video. The RNN architecture frequently includes cyclic connections, which enable the RNN to update its current state based on prior states and new input data. On specific challenges, these networks, which are composed of typical recurrent cells (such as sigma cells), have excelled. Completely RNNs, limited Runs, and Jordan, 1986, all serve as examples (Elman, 1990; Chen & Soo, 1996). Unfortunately, when there is a sizable gap between the crucial input data, the aforementioned RNNs cannot link the relevant data. Long short-term memory was favored by Hochreiter and Schmidhuber (1997) to handle “long-term dependency” (LSTM). Figure 21 shows the structure of LSTM (Yu et al., 2019).

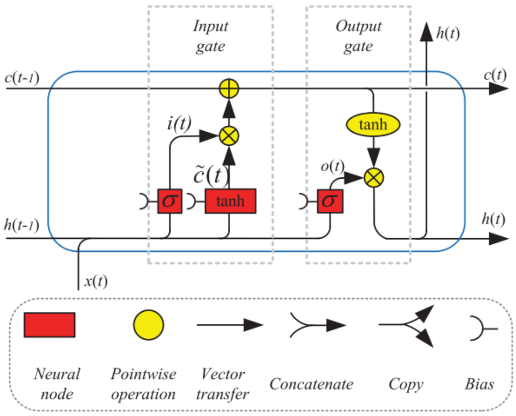



**Figure 21.** LSTM structure.

### 5.4. Support Vector Machine

By studying hundreds or thousands of reports of both fraudulent and legitimate credit card activity, a SVM is a computer method that can learn to identify fraudulent credit card activity. Using a sizable database of scanned images of handwritten zeros, ones, and other numbers, an SVM can also be taught to recognize handwritten digits. A mathematical object known as an SVM is a technique for maximizing a specific mathematical function with respect to a specific collection of data. However, it is feasible to explain the fundamental concepts underlying the SVM algorithm without having to read an equation. In fact, we contend that only four fundamental ideas—the separating hyperplane, the maximum-margin hyperplane, the soft margin, and the kernel function—need to be comprehended to completely understand the fundamentals of SVM classification. Figure 22 shows the structure of SVM (Noble, 2006).

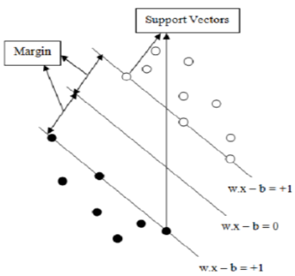



**Figure 22.** SVM structure.

### 5.5. Genetic Algorithm

An adaptable heuristic search technique built on population genetics, the genetic algorithm. John Holland developed the first DNA code at the start of the 1970s. A probabilistic search method built on the principles of natural selection and heredity is known as a genetic algorithm. The population in a genetic program is the starting set of answers. Chromosomes serve as a symbol for solutions. The population number remains constant over generations. The fitness of each chromosome is assessed after each generation, and the chromosomes for the following generation are then probabilistically chosen based on their ratings. Many of the chosen chromosomes randomly mate and have children. Random crossings and mutations occur during reproduction. Since chromosomes with high fitness values are more likely to be chosen, the average fitness value of the chromosomes in the current generation may be higher than that of the chromosomes in the preceding generation. Up until the last requirement is met, the evolutionary process continues looping back and forth. Chromosomes or sequences are common terms for the products of genetic processes. Figure 23 shows the structure of GA (Kumar et al., 2010).

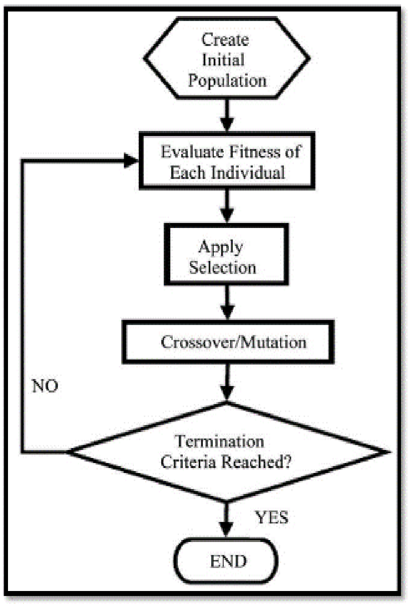



**Figure 23.** GA structure.

### 5.6. Fuzzy Systems

Since fuzzy systems have been used in commercial applications, developers are aware that it is not always simple to build a successful fuzzy system. Finding the right membership functions and fuzzy rules can be a time-consuming, trial-and-error procedure. As a result, the notion of using learning methods with fuzzy systems was regarded as an early method for creating so-called adaptive or self-organizing fuzzy controllers. These flexible models frequently employ knowledge-based techniques. Neural networks, however, offer yet another option for discovering ambiguous system parameters. Because of their ability to learn, neural networks are a good candidate for pairing with fuzzy systems to automate or support the process of creating a fuzzy system for a particular job. Figure 23 shows the structure of Fuzzy system (Nauck, 1997).

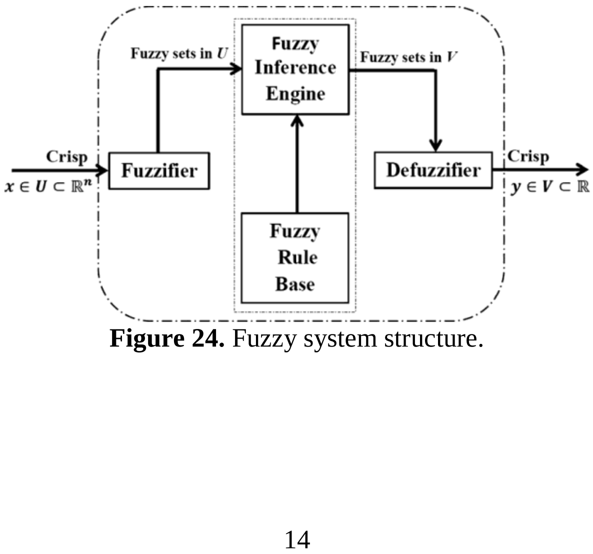



**Figure 24.** Fuzzy system structure.

## 6. COLOR SPACES

In this section, color theory and color spaces are mentioned.

### 6.1. Color Theory

When an object is observed in the presence of a specific light source, the reflected wavelength of the object has a physio-psychometric influence on the observer’s brain. The term “color theory” referred to a standardized scientific method with a specific mathematical or empirical formula with arrangements of incidence of light/standard illuminant for absorption and reflection of the color on and from the object, followed by detection, followed by measurement of color value specific reflectance, or any other quantified values to record and communicate color information for reproducibility and matching (Samanta, 2022).

Color is a feature of visual perception that can include any combination of chromatic and achromatic content, according to the CIE definition. Both chromatic and achromatic color names, such as white, gray, or black, can be used to describe this property. Chromatic color names include pink, brown, yellow, orange, green, red, blue, and purple. Additionally, it can be described by combining these titles. The structure of the color detection screen with RGB is shown (Samanta, 2022).

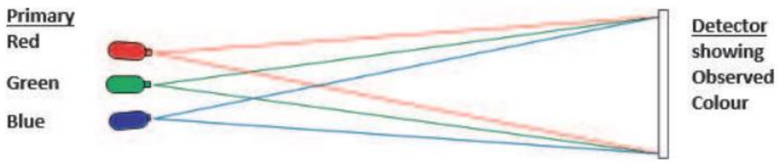



**Figure 25.** Color detection display with RGB.

The process of measuring and evaluating color value in any measurable terms is known as colorimetry. It allows us to translate the physio-psychological perception of color that is experienced by our eyes into a real physical measurement. As a result, the hue of any object can be thought of as a physiological and psychological illusion caused by radiation or visible light that has been deflected from a material or object after light has struck it (Samanta, 2022).

### 6.2. CIE 1931 Theory of Colour

The Commission Internationale de l'Éclairage (CIE) has suggested x(l), y(l), and z(l) for [360 nm, 830 nm] in 1 nm steps for color discrimination based on generally accepted tristimulus values. By combining the RGB’s three fixed primary colors additively, a variety of color stimuli can be precisely matched in color across a wide range of observational conditions. These additive mixtures combine linearly, symmetrically, and transitively and can be expressed as stimuli of any hue detected under standard illumination under standard detection using three coordinates known as Tristimulus values. Figure 26 shows the calculation of Tristimulus values. (X, Y, and Z) (Samanta, 2022).

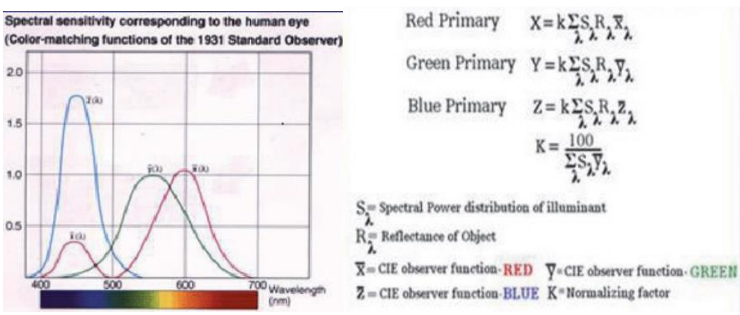



**Figure 26.** RGB primary stimuli’s effect on the human eye’s spectral sensitivity, and the actual measurement of an object’s reflectance and associated Tristimulus values that follow.

### 6.3. CIE 1976 Theory of Colour

L*, a*, and b* values should be used to evaluate color differences between two samples of the same or similar textiles, according to the 1976 CIE L*a*b* color space. The 1976 CIE L*a*b* color space diagram depicts the total color differences value by E or E*. The 1976 CIE scale of redness (+a*)/greenness is represented by -a*, the 1976 CIE scale of yellowness (+b*)/blueness is represented by -b*. These scales resemble the Munsell Value scale of lightness dispersion more or less (Samanta, 2022).

Devices called spectrophotometers are used to detect an object's color. To determine the color that shows in relation to an object's reflection, these devices frequently employ a recognized technique. Since we use x to depict colors using vector points in three-dimensional space, what we refer to as the color space in mathematics is essentially y and z for position coordinates. Specific values of how red, green, and blue it is in relation to a reference location are shown here as coordinates. Figure 27 shows the structure of the CIELAB space. (Which may differ between color spaces) (Zhu, 2022).

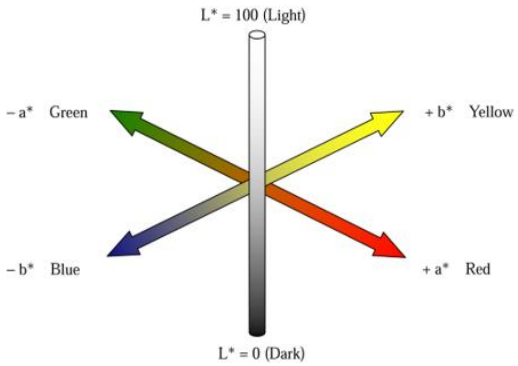



**Figure 27.** CIE L*a*b* color space.

Commonly, standard color spaces include the CIELAB color space or CIEGYZ color space, which were designed to encompass almost all colors that can normally be observed as humans (Zhu, 2022).

### 6.4. Properties of the CIE L*a*b* color space

CIELAB Color Space: L*, a*, b*, c*, h values are the main parameters used to define colors in the CIELAB color system (CIE 1931 XYZ Color Space).

L*: Luminance value. It is the perpendicular axis in color space. It is 0º for black and 100º for white. This varies between the two values the L* value increases, the brightness of the color increases (CIE 1931 XYZ Color Space).

a* and b*: Chromatic coordinates. In the CIELAB color space, +a* indicates the red direction, -a* indicates the green, + b* indicates the yellow, -b* indicates the blue (CIE 1931 XYZ Color Space).

When the literature was scanned for recipe estimation, it was seen that this color space was used.

## 7. SPECTROPHOTOMETER AND HYPERSPECTRAL CAMERA

The sample's reflectance at each wavelength is measured independently by the reflectance spectrophotometer. For color measurements, it logs reflectance in the 400–700 nm visible spectral area at the necessary intervals of 5 nm, 10 nm, and 20 nm. For textile samples, measurements have been made in the spectral region from 400 to 700 nm at 20 nm intervals (Samanta, 2018).

### 7.1. Calibration of Device

In order to get the instrument back in working order, calibration is carried out. Between maximum reflectance (100% white) and maximum absorption (100% black), color (Visible light-400nm-700nm) is measured. The device scans a standard white tile and a standard black tile in order to configure these parameters (Samanta, 2018).

An arriving batch can be compared to your current criteria in quality control. Results that follow can be observed in terms of tone and strength. The samples are thoroughly examined in terms of their hue, lightness, saturation, and general placement in the color space index. You can analyze the measured samples using graphs and statistics thanks to quality control (Samanta, 2018).

### 7.2. Hyperspectral Camera

Due to new developments in digital imaging technology, spectral imaging technology is now acknowledged as a unique method of color matching and evaluation. To accurately evaluate the interior and external properties of samples, spectral and imaging technology are combined in a hyperspectral imaging system (HIS). As a result, information in three dimensions is gathered about the observed samples, such as their spatial location, spectral power, and frequency. The remote food monitoring, sensing, and medical device sectors are the main users of this (Zhang et al., 2021).

Zhang et al., (2021) used an HIS for the first time to quantify the multi-colors of printed fabric in 2019. The technology helps to correct uneven or multicolored measurements and can correctly measure the colors and spectral characteristics of colorful textile products. The HIS system does have some disadvantages, though, such as data redundancy, enormous storage space consumption, and a strong correlation between band spacing, which are all caused by how much data it collects. As a result, good spectral matching results cannot be achieved when processing hyperspectral data using the traditional spectral matching algorithm. Deep learning technology has quickly developed in recent years, leading to the creation of numerous data-processing methods. Processing spectrum data using deep learning-based algorithms is one such effective strategy.

Salazar-Vazquez and Mendez-Vazquez (2020) used modern high-resolution cameras, circuitry, and optics in 2020 to develop a dependable, affordable, and straightforward HSI device. This tool could be used to evaluate the feasibility of developing new apps on a tight budget and to evaluate new hyperspectral image processing algorithms. It can detect wavelengths between 400 and 1052 nm, generate up to 315 distinct wavebands, and have a spectral precision of up to 2.0698 nm. It can weigh up to 300 g. Its spatial resolution of 116 110 pixels is useful for many uses. Furthermore, it has shown excellent spectrum precision in both controlled and natural light settings while costing only 2% as much as commercial HSI devices with equivalent capabilities.

The suggested HSI system contains a framework to create the proposed HSI from scratch, in contrast to similar studies. The processing speed and complexity of creating an HSI device are both reduced by this design. It includes every 3D model required, a calibration technique, image acquisition software, and the construction and calibration process for the suggested HSI device. As a result, the suggested HSI system is lightweight, transportable, and reusable (Salazar-Vazquez and Mendez-Vazquez, 2020).

## 8. COMPARISON OF DYEING RECIPE PREDICTION STUDIES

About 20 articles were examined comparatively in this section. The latest methods and datasets related to recipe prediction are indicated. In the literature study, a publication was shared about the processes in large boilers other than laboratory processes.

**Table 2.** Latest methods and datasets.

| Authors | Year | Method |
|---|---|---|
| Sagirlibas | 2009 | Fuzzy logic and ANN model were used to predict the description of the color. The data groups used for these estimates were formed using the CIE system (Lab, Lch, XYZ) and reflection values. The color description was calculated using various programs created in matlab, including fuzzy logic, feed-forward multilayer sensor neural network, and radial basic function neural network (RBF NN), and the results were compared extensively. |
| Onar | 2011 | The Kubelka Munk method and ANN model were applied and compared. 342 training data 23 test data were used. The study was conducted in MATLAB. The ANN models have shown better results. |
| Zhu | 2022 | A three-layer neural network model can be used to forecast the hue of a cotton fabric once it has dried. Several models have been developed in line with the clamping pressure, with the models’ expected values for L*a*b* in the dry state serving as their outputs and the reflection values of L*a*b* in the wet state serving as their inputs. |
| Qin and Zhang | 2021 | The multiple gradient boosting regression tree model (GBRT) was used in this investigation. With the data collected for three different color spaces, it has been trained and evaluated. It uses the D65 light source, which contains 810 data. |
| Westland | 1998 | 123 educational and 40 test data were used. A MLP model was used. |
| Kandi | 2007 | A novel approach to predicting color recipes using genetic algorithms is put forth. Based on its fitness function, this approach can perform both spectrophotometric and colorimetric color matching. |
| Chaouch et al. | 2020 | A fresh approach to utilize a genetic algorithm to tackle the color recipe prediction problem is put forth. 100 data sets were used. |

| | | |
|---|---|---|
| Chaouch et al. | 2019 | Ant colony optimization is used to introduce a novel method for color recipe prediction. To dye, samples of fabrics made entirely of cotton were utilized. |
| Li et al. | 2022 | This paper uses a novel feature-weighted support vector regression and particle swarm optimization method for fabric dyeing recipe prediction. The experiment used dyeing data based on two distinct materials (cotton and taffeta). |
| Sennaroglu et al. | 2014 | An ANN technique was employed in this study to forecast the color recipes that would match the reference colors of knitted fabrics made entirely of acrylic. A multilayer sensor network makes up the created neural network. The intended outputs are dye concentrations, and the inputs are spectral luminance factors at wavelengths ranging from 400 nm to 700 nm at 10 nm intervals. |
| Zhang et al. | 2021 | A deep learning algorithm and hyperspectral color measurement-based dyeing recipe prediction model for cotton fabric have been suggested. There were 363 data used in total. Results from the suggested model and the Datacolor 650 spectrophotometer were compared. |
| Tu et al. | 2022 | For this categorization, a straightforward but successful methodology is presented in this study. To identify categories of fabrics with comparable coloring characteristics for a particular combination of dyes, the method employs the classic K-Means clustering analysis. It has been utilized as a stage in the preparation of data, and an analysis of the literature reveals that it is one of the significant researches. 28 different types of fabrics have been found to be grouped into 8 groups based on their colour characteristics. |
| Yu et al. | 2021 | Three single reactive dye databases were made by dyeing various cotton knitted materials and a number of dyeing strategies were established. The color parameter L*, a*, and b* values of dyed materials were used as model inputs, and a model based on PSO-LSSVM was also built, which uses dye concentration as a model output. It was discovered that the estimated values of the PSO-LSSVM models for the color parameters L*, a*, and b* of the dyed fabrics at the dye concentration agreed with the actual measured values of the tested cotton fibers. |
| Chen et al. | 2021 | This study provides an automated color matching prediction model, CMR-Color, by merging three neural network models, including conventional CNN, MLP, and ResNet, in order to improve the ability to derive high-dimensional features from spectral data. The 72,132 recipe data originate from a well-known company mentioned in the textiles industry. |
| Chaouch et al. | 2022 | This article presented and compared evolutionary algorithms for color recipe prediction, in particular ant colony and genetic algorithms. In this study, three reactive dyes (100% cotton) were used for dyeing woven fabrics. |
| Ku et al. | 2020 | A decision support system for scheduling dyeing machines was designed to increase intelligent production and dismantle information silos. It did this by using a framework as a systematic technique to gather, identify, and analyze relevant processes and decisions for an organization. Installation time, particularly for textile dying processes, is order-dependent, and installation for tank cleaning is needed for goods of various types and colors. The outcomes showed that Industry 3.5 and the suggested approach were applicable in real-world situations. The designed method has been put into practice in a textile business in Taiwan. |

## 9. CONCLUSION

It has been seen that creating a color recipe for computer-aided fabric dyeing gives better results with the help of a literature study. ANNs have been tried for computer-aided color recipe and good results have been obtained. Recently, the use of measurements with a hyperspectral camera and the elimination of dependence on a spectrophotometer have shown good results for researchers. It has also shown better results with the use of LSTM models. In the studies conducted, it has been seen that in real life, it is an optimization problem for us to extract higher quality recipes from cheaper dyes due to the restrictions of the company. In addition to the literature study, the process of creating a recipe at a textile dyeing company in Istanbul was carried out and explained step by step.

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