



Vision-Based and Machine Learning Approaches for Real-Time Dye Concentration Monitoring in Textile Processes: A Review

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Abstract: The textile industry is one of the most significant industries in Sri Lanka, which gives a massive economic income to the country. Dyeing is an important process in the apparel industry since it directly impacts the exports if it does not have the accurate color consistency that's needed. Such inaccuracies in color consistency lead to poor product quality, which affects the reputation of the brand and customer satisfaction. The most common method of measuring color concentration is using the UV-Vis spectrophotometer. It's accurate but high in cost and needs trained professionals for operation. This study shows the advantages and disadvantages of existing traditional methods and how newly developed methods show enhancement in process efficiency. Smartphone colorimetry has been introduced as a new approach, but it still lacks some features to be used in a fully automated industrial environment. Vision-based machine learning systems are known to predict dye baths under controlled lighting conditions in automated industrial environments, where image processing techniques will extract relevant color features (RGB values). These values will be analyzed using machine learning algorithms trained by using laboratory reference data. This will allow for timely adjustments and process optimization. This paper addresses how the textile industry can enhance its process efficiency by knowing the strengths and limitations of different techniques of monitoring dye concentration. It also demonstrates how future expansions can be made by developing a low-cost, fully automated system using machine learning integrated with vision-based systems which can enhance the system's accuracy, and it's affordable and automated. The right color consistency will help in better dye usage and less material waste. Expected benefits are improved process control and cost-effective automation aligned with AI-driven solutions. This paper shows economically affordable and sustainable textile production practices.

Keywords: Dye Bath Monitoring, Low-cost, Machine Learning, Textile Automation, Sustainability, Vision-based.

1 INTRODUCTION

The textile industry is one of the major industries in the country. Dyeing is a crucial part of the apparel industry. Having the right color consistency is important during this process, as it will help in achieving the desired color. Inaccurate control of dye bath concentration will lead to wastage of dye and rework, thereby reducing environmental impact. Some of the existing methods for monitoring concentration rely on taking samples and analyzing them in a lab with UV-Vis spectrophotometers. They are reliable, sensitive and accurate, but they do not work well for continuous process control due to their cost, sampling delays, and the need for trained staff [1], [2]. Some recent studies have shown that alternatives like chemometric methods such as Principal Component Regression (PCR) and Partial Least Squares (PLS), can be used in the analysis of complex dye mixtures where multiple dyes are present [1]. UV-Vis microspectrophotometer also been introduced to enhance the process by measuring almost indistinguishable substances under the optical

microscope [3]. Raman spectrophotometry shows that molecular structural information can be used to identify and differentiate dye compounds in complex mixtures [4]. Further developments have found sensing technologies that are portable and lower in cost, such as smartphone/camera colorimetry. They are not only affordable but also easier to use compared to traditional UV-Vis spectrophotometers. They show that accurate estimation of dye concentration can be done by linking image data with spectrophotometer values [5]. Proper management of lighting, optimization of camera settings and rigorous calibration improve the reproducibility of smartphone colorimetry. Even though some of the recent developments show that the use of smartphone/camera colorimetry can be a better substitute [6], only a few present an integrated process-level ML-driven system that provides continuous dye bath monitoring. Machine Learning methods have improved the capability to model nonlinear relationships between visual features and analyze concentrations simultaneously. It has made systems more flexible to noise and changes in lighting. Therefore, to improve color consistency and have an affordable operating system, a smart, real-time, vision-based machine learning system can be used. It will be beneficial, especially for small and medium enterprises in Sri Lanka.

2 TRADITIONAL MEASURING METHODS

The traditional methods of measuring the concentration of dyes in the textile industry are primarily based on UV-Vis spectrometry and analytical methods. UV-Vis spectrometry is known as the most used method for its high accuracy, repeatability, and high sensitivity. This method is widely used in the textile industry to identify different dyes and their concentrations. UV-Vis spectrophotometry is an analytical technique that is used to measure how much light a chemical substance absorbs. Therefore, absorbance and the maximum wavelength of the substance are measured through it. Spectrophotometry follows the principle of the Beer-Lambert Law. It states that the absorbance of light by a solution is directly proportional to the concentration of the substance and the path length of the light through the sample. Beer-Lambert Law is expressed as:

$$A = \epsilon Lc \quad (1)$$

In equation 1, A represents Absorbance, ϵ represents Molar Absorptivity (a constant for a given dye), L represents the path length of the light through the sample, and c represents the concentration of the dye.

Numerous types of dyes are used in the textile industry, which are dissolved in aqueous solutions. These dyes absorb light at specific wavelengths where the absorbance is measured. Then that measured absorbance is used to determine the concentration of the dyes through a calibration curve. Therefore, UV-Vis spectrometry is the most used technique due to its possibility to obtain highly accurate results while being simple and reliable [1],[2]. Advanced approaches such as PLS (Partial Least Squares) and PCR (Principal Component Regression) have been integrated along with UV-Vis measurements to reduce the complexity in dyeing processes where multiple dyes are present simultaneously. These techniques allow us to measure multiple dyes simultaneously by analyzing spectral data of multiple wavelengths, thereby enhancing the prediction accuracy in complex mixtures [1].

Furthermore, more advanced analytical techniques like UV-Vis microspectrometry and Raman spectroscopy have been tested for analyzing dyes. UV-Vis microspectrometry is used to measure how a substance that's being examined interacts with ultraviolet and visible (UV-Vis) light at multiple wavelengths by analyzing the amount of light absorbed or transmitted through microscopic or very small areas. It gives a detailed analysis

of the substance's optical properties and composition. UV-Vis Microspectrometry is useful in studies where slightly colored or almost indistinguishable substances under the optical microscope are used [3]. Raman spectroscopy can be used to obtain molecular structural information of a dye as it identifies and differentiates dye compounds in complex mixtures [4]. These methods show improved analytical capabilities, but they require different instrumentation and controlled laboratory environments.

Even though these traditional methods are highly accurate and reliable, they have some limitations when it comes to real-time industrial monitoring. Traditional methods contain many manual steps, such as sample collection and preparation, which leads to interrupting the dyeing process and delaying the result obtaining process. The instruments used in traditional methods mostly aren't portable and are very high in cost. They also need trained staff for operation and data collection, which limits their applicability in industrial environments where continuous service is needed [2]. These traditional spectrophotometers are not designed to be used in situations where real-time monitoring is needed, which is essential in enhancing the dyeing process efficiency and maintaining consistent dye quality. Due to these limitations in the instruments of the industry, some advanced alternative approaches have been developed. Vision-based systems and machine learning techniques have been found as alternatives that enhance the process by providing rapid, real-time analysis of dyes while maintaining acceptable levels of accuracy of results. These instruments are also cost-effective when compared to traditional spectrophotometers, and they do not need trained professionals for operation.

3 VISION BASED COLORIMETRIC METHODS

Advanced alternative approaches have been found that uses portable electronic devices along with different imaging technologies to monitor dye concentrations. These vision-based colorimetric systems use smartphones or cameras to capture pictures and gather color information from the given dye solutions. Then that information is used to estimate the dye concentration using image analysis. Unlike UV-Vis spectrophotometers, these techniques use portable, low-cost instrumentation to ease the process of operation. They also do not need trained staff for operation and are specifically designed to provide real-time and on-site monitoring of substances/dyes. Vision-based systems work by capturing images of dye samples and by extracting color features (RGB values) known as Red, Green and Blue intensity values. These values are then correlated with dye concentration through calibration models developed using samples with known concentrations. Since the color intensity of the solution depends on its concentration, vision-based systems can be used as a better alternative to traditional spectrophotometers [5].

3.1 Smartphone/ Camera-based colorimetry

In smartphones, colorimetry smartphone cameras are used as a sensing device or the colorimeter, as it is easily portable. Smartphone colorimetry instruments are easier to use since it involves familiar technologies. Several studies have shown that using smartphones can achieve almost similar results as the UV-Vis spectrophotometer. Smartphones have built-in white LED lights and digital cameras, which help in achieving good colorimetric assessment. It can be done by shining the LED light on a sample and detecting the reflection of it. For better results, a clip-on dispersive grating can be used, which will enable spectral analysis to get more accurate results. In most of these playstore apps have been used to extract the RGB values which is very convenient [6].

Another low-cost smartphone-based spectrophotometer was developed where a paper structure and a DVD

fragment were used as a diffraction grating for dye detection and a mini-LED as the light source. This system used the smartphone camera to capture spectral information and to estimate dye concentration. This device depicts that it can be used as an accurate and precise device for dye detection. This is a low-cost, portable alternative approach that can also be used by non-trained personnel compared to a UV-Vis spectrophotometer [7].

Furthermore, some developments were made where the solidified floating organic drop microextraction method (SFODME) was combined with image-based colorimetry for detection of the dyes [8]. In this method, a smartphone camera is used to capture sample images after the extraction of solvent, where RGB channel analysis was done to estimate its concentration. It showed that the green color channel had the strongest linear relationship with dye concentration. Therefore, the green color channel was selected for quantification. Even though this technique achieved an acceptable rate of accuracy, it still had some downfalls, such as uncontrolled lighting conditions and camera variations.

Vision-based colorimetry mostly has acceptable accuracy rates, but it also has some limitations. One of the most commonly seen challenges is the uncontrolled lighting conditions, which affect the accuracy of the results of dye concentrations. Since the color of the captured images may vary according to the lighting conditions present, the results may not be as accurate as they should be. Therefore, it's hard to produce the best results in industrial environments where lighting conditions change continuously. There can also be variations in camera sensors and the image acquisition settings, which also affect the accuracy of the results. Nevertheless, smartphone/ camera-based colorimetry gives many advantages over the traditional laboratory techniques. They are less expensive, portable and can be used without any trained personnel. Since vision-based techniques include image processing and computational techniques, it allows rapid analysis of the substance. Since some limitations, such as lighting conditions and non-linear color concentration relationships, have arisen, advanced developments have been found where machine learning techniques have been integrated into vision-based systems.

3.2 Machine Learning applied to colorimetric predictions

Machine learning has been integrated into vision-based colorimetric systems to enhance their performance by reducing their limitations. Conventional calibration methods mostly struggle with non-linear relationships between color intensity and concentration, mostly due to variations in the lighting conditions and sample compositions. Therefore, machine learning techniques have been integrated into vision-based colorimetric systems to improve their performance. They also help in reducing the process time by eliminating manual inspection [9]. They enhance its accuracy, robustness and adaptability by learning complex patterns directly from image and spectral data to reduce its limitations. When it comes to machine learning techniques for colorimetric predictions, there are a few models that can be trained to get the most accurate predictions. Linear Regression, Random Forest, Artificial Neural Network (ANNs) and Deep Neural Networks (DNNs) are such models [10]. These models can analyze and differentiate color information and develop relationships between image features and the target variables such as turbidity, color quality and dye concentration. Therefore, studies show that these models can be used in textile color prediction, for instance, at times where you must predict dry fabric color from wet fabric color measurements [10].

Machine learning techniques have been integrated with smartphone-based colorimetric systems to enhance dye and chemical analysis. Color changes captured through smartphone cameras are analyzed using machine learning models, and RGB features are extracted to analyze concentrations. This helps reduce errors caused

by of limitations such as different lighting conditions, camera settings, and environmental noises [11]. This way, a low-cost, more stable and accurate system can be formed. More studies show that machine learning models have been integrated with vision-based systems to monitor water quality and turbidity. Camera-based sensing systems have been developed where real-time wastewater quality monitoring can be done using optical analysis and image acquisition. They show that such camera-based systems are inexpensive and can continuously monitor variations in water quality parameters in a non-contact manner [12]. Therefore, this shows that such systems can provide efficient and accurate analysis compared to traditional methods. A smartphone-based machine vision framework to estimate water turbidity using images captured from a smartphone camera depicts that machine learning algorithms can accurately predict turbidity levels from image features. Even with some limitations like lighting conditions and environmental changes, it has proven that it can successfully predict turbidity using machine vision [13]. This proves that smartphone colorimetry, together with machine learning algorithms, can successfully develop a portable device that can monitor and predict turbidity water quality. Another study demonstrates a machine vision system that is designed to estimate turbidity using underwater images. Using computer vision along with predictive algorithms to analyze image characteristics to predict turbidity levels in real-time proves that it can be used for continuous environmental monitoring under varying image conditions [14].

Moreover, some studies show that machine learning models like artificial neural networks (ANNs), optimization algorithms and fuzzy logic systems can be used to improve textile color prediction more accurately than traditional methods [15], [16]. Therefore, machine vision systems can be used in industrial environments where automated real-time monitoring and prediction are needed. ML techniques have mostly been integrated with sensing systems to improve predictive accuracy, pattern recognition and automated decision making. They can be used to identify and analyze complex nonlinear relationships that are difficult to understand through traditional calibration methods. Studies have shown that intelligent predictive models can improve sensor performance, real-time analysis and decision making in complex sensing environments [17].

Machine learning applied to colorimetric predictions shows many advantages compared to traditional techniques, as they are portable, lower in cost, and can address complex nonlinear relationships while producing acceptable rates of accuracy of results. But when training a machine learning model, a large dataset is needed. If proper calibration isn't done, lighting conditions, camera settings and sample positioning can still affect its accuracy. Therefore, proper calibration is very important. Furthermore, training machine learning models consumes a certain period and need good computational resources to be developed properly. Even though there are some limitations, ML applied integrated with colorimetry shows that it can be used in monitoring and predicting textile dye concentrations in industrial environments where continuous, real-time monitoring is needed.

4 COMPARATIVE ANALYSIS

Comparatively, when all these techniques are considered, there are advantages and disadvantages. The comparison is focused on different kinds of concentration monitoring techniques that are available according to their performance, accuracy, portability, processing time and real-time capabilities. This comparison will demonstrate the strengths and limitations of each method.

Table 1 Comparison of different techniques of measuring dye concentration

Technique	Strengths	Limitations	Real-time monitoring	Cost
UV-Vis Spectrometry	Highly accurate	- Expensive - Laboratory based	No	High
Smartphone/ Camera-based Colorimetry	- Portable - Low cost - Robustness	Lighting sensitivity	Yes	Low
ML applied to Colorimetric Predictions	- High prediction accuracy - Robustness - Can be used in different environmental conditions	- Requires large set of data for training - Takes time to train a model	Yes	Medium

Therefore, Table 1 summarizes the features of different techniques used for dye monitoring and prediction. UV-Vis spectrometry provides high accuracy, but it's very expensive, while vision-based techniques offer low-cost systems with real-time monitoring, but are light sensitive. ML applied vision-based systems enhance the accuracy of prediction by analyzing non-linear relationships from image data while monitoring it in real time.

5 CHALLENGES AND LIMITATIONS

Even though developments have been made in vision-based machine learning systems, there are still some limitations to be addressed to achieve a fully automated system where dye concentration can be measured. Since images are captured and used to predict the dye concentrations in vision-based systems, the lighting conditions of the image matter a lot. Therefore, it's important to have a consistent lighting setting in the system. Differences in surrounding light, shadows or any reflections can affect the features of the captured image, which can lead to inaccuracies in the final predictions. Camera settings of the camera used in the system should also be very consistent, as it affects the accuracy of the predictions. Any differences in camera sensors, white balance settings and image acquisition parameters can reduce the reproducibility between the devices.

Another major challenge is frequent recalibration that must be done to maintain the system's stability. The system needs to be recalibrated frequently for it to adapt and give accurate predictions in different environmental conditions. Moreover, nonlinear relationships between color intensity and dye concentration may limit the effectiveness of traditional calibration models. For vision-based ML models, there needs to be a large data set for them to be trained [18]. Machine learning models totally depend on the data that they are being trained on. Therefore, having a large and diverse data set that represents real industrial conditions is

important. Small or insufficient data sets may reduce the accuracy of the model. ML models also need high computational power, longer training times and memory resources, which are challenging when being implemented on low-power embedded devices. Therefore, implementing deep learning systems in some real-world industrial environments is a bit challenging [19].

Moreover, there can be variations in dye compositions, temperature, pH, turbidity and water quality, which can influence image quality thereby affecting the accuracy of the predictions.

6 FUTURE RESEARCH DIRECTIONS

Future expansions in monitoring dye concentrations in the textile industry should be focused more towards developing a real-time automation system where intelligent sensing technologies and machine learning are integrated. Therefore, developing such a system where real-time monitoring is offered in varying environmental conditions is beneficial.

Advanced machine learning and deep learning techniques such as Convolutional Neural Network (CNNs) can be beneficial as they are said to improve feature extraction, nonlinear modeling relationships and accuracy of predictions in varying environments. Integration of edge computing and embedded AI platforms, like low-power intelligent processing devices, offers significant potential for real-time monitoring applications. Furthermore, including AI vision-based sensing, spectroscopy and IoT-enabled sensors can improve real-time monitoring and prediction in industrial sites [20]. Moreover, if feedback control mechanisms can be integrated in these systems it would be capable of adjusting dyeing parameters depending on their sensor predictions. Such features can improve overall system performance and efficiency in the textile dyeing process. This will help in reducing dye waste, minimizing water consumption, while enhancing product consistency.

7 CONCLUSIONS

This paper addresses different techniques of monitoring concentration of dyes in the textile industry, such as traditional spectrometry, vision-based systems and machine learning applied to vision-based systems. Traditional UV-Vis spectrometry is the most used method. It provides high analytical accuracy but is expensive and needs laboratory facilities. They also need trained staff for operations and cannot monitor dye concentration in real-time. Vision-based systems are lower in cost, portable and provide real-time monitoring through smartphone cameras, digital imaging and RGB analysis.

Some new developments have shown that Machine Learning integrated in vision-based systems has enhanced their performance by improving their prediction accuracy, robustness and automated decision making. Machine Learning models like random forest, neural networks and deep learning models have proved that they can handle complex nonlinear relationships between different parameters. Even though there are some limitations regarding illumination sensitivity, calibration stability, dataset requirements and industrial implementation, machine learning applied to vision-based systems is a great source to monitor and predict dye concentrations in real-time in varying industrial environments. Therefore, developing a low-cost, portable system integrated with intelligent sensing, embedded AI and automated process control, which can accurately predict dye concentrations in textile industries, would be a great approach to improve the feasibility of the existing systems.

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