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Image Colour Correction of Smartphone-based Imaging Devices for Medical Application: A Literature Review

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Abstract:
Smartphone technology has revolutionised the field of digital imaging, especially in healthcare and medical applications. Smartphones equipped with built-in high-resolution imaging capabilities, smartphone-based imaging devices have become cost-effective and powerful tools for health monitoring and diagnosis. However, the colour information of the images captured by different smartphone models varies from one to another, which introduces the colour distortion. These colour distortions may negatively impact image interpretation, diagnosis accuracy, and subsequent deep learning based medical analysis. In this context, the field of colour constancy algorithms has become extremely important in providing accurate and consistent colour representation in digital images. Colour constancy has gained significant scientific interest in the last two decades due to its crucial role in mitigating colour distortions caused by varying image acquisition conditions. These algorithms are essential pre-processing steps to standardise colour representation across different devices and imaging conditions, thus reproducing images that accurately represent real-world scenes. Over the years, many studies have been conducted on the colour constancy topic to improve its effectiveness and accuracy in various domains. This paper reviews significant contributions to colour constancy algorithms over the past 10 years, including the fundamentals of image formation, colour correction algorithms in conventional applications, and colour correction algorithms in the medical field. By offering a comprehensive overview of these key topics, the paper highlights the potential of smartphone-based imaging and colour constancy algorithms in advancing healthcare applications and enhancing diagnostic accuracy.

Keywords: Colour constancy; Colour correction; Digital imaging; Smartphone-based imaging devices

1. INTRODUCTION

Evolutionary leaps in healthcare technology not only result in expanding options for medical treatment but also transform how clinicians perform their jobs. There is no doubt that human health and high-quality imaging modalities are inextricably linked to one another, as medical images or videos on display are great tools to provide accurate anatomical information, which can play a vital role in early-stage detection and help make better treatment decisions remotely instead of through direct viewing of the subject. Medical images can be categorised as greyscale, false colour, and true colour. In the past, greyscale medical images, such as X-rays, magnetic resonance imaging (MRIs), and computed tomography (CT) scans, were commonly used for diagnostic purposes. With the advancement of medical imaging devices, medical images are no longer restricted to greyscale modalities. True colour medical images are becoming more and more popular, as colour is also considered an important criterion for providing medical diagnostic value. By analysing colour features and colour differences extracted from colour medical images, physiological information about the human body's condition can be retrieved. Hence, simple, portable, telemedicine-enabled imaging tools, such as smartphone-based imaging devices (SIDs), have been introduced as optimal routine monitoring tools. Scanning image detections (SIDs) are not only conceivable in the context of remote monitoring, but other medical areas could also benefit, especially in specialities such as ex vivo diagnostics, in vivo diagnostics, oriental medicine (1–5), dermatology (6), video endoscopy, and ophthalmology (7–10).

Scanning image detections offer the possibility of enabling more efficient, targeted, and patient-friendly medical care without compromising quality. Unfortunately, a wide range of SID applications is still in the developing stage, and most of them have yet to undergo standardisation. Furthermore, the final quality of the image is easily affected by a plethora of factors. Variations in illumination conditions, device calibration, and operator dexterity are the main factors impacting the final appearance and quality of the image (11). This phenomenon causes the procedure of interpreting colour medical images to become intricate. Based on the aforementioned issues, colour constancy algorithms have been introduced to

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reduce quality variability in medical images and deliver reliable information to clinicians for routine monitoring. Colour constancy is the ability of the human colour perception system to perceive stable object colour, despite spatial and temporal changes, as well as spectral changes in the illumination (12). The process of colour constancy involves transforming the colour of images acquired under unknown light as if they were acquired under defined light conditions, usually perfect white light. Many researchers are engaged with the topic of colour correction for colour correction.

This manuscript discusses various colour correction methods for colour constancy reported by previous research. The techniques were categorised into conventional applications and medical applications. The comparison between the performance of each colour correction method is also presented to select the best colour correction techniques that could work robustly and conveniently in various conditions. Section 2 discusses the research methodology that comprises the search engines used to gather the research papers and colour correction methods implemented in the conventional and medical field. Section 3 briefly introduces the principles of image formation. Section 4 presents various colour correction methodologies for conventional and medical usage. The discussion on the colour correction methodologies is shown in Section 5. This paper concludes in Section 6 with suggestions for future work.

2. RESEARCH METHODOLOGY

This review was conducted using a few scholarly databases such as PubMed, Web of Science, Google Scholar Search, and ResearchGate to find articles, journals, conference papers, thesis dissertations, books and book chapters related to colour constancy, colour correction, colour normalisation, colour standardisation, image white balance, illumination estimation, lighting environments, colour patches, light conditions, colour space, colour distortion, colour analysis, correction matrix, and colour space. The review also focused on colour correction applications in the medical field by searching on the keywords: ‘tongue imaging device, tongue analysis, dermoscopic, digital pathology, digital dermatology telemedicine, oriental medicine, traditional Chinese medicine, medical facial analysis’ up to December 2024 without any restriction on the article type and the date of publication.

An initial pool of approximately 80 articles was retrieved based on keyword searches. The manuscripts were selected by reading the title, abstract, and conclusion to catch the terms and methods related to the proposed research. After this preliminary screening, 50 articles were shortlisted for full-text review based on relevance to colour correction techniques and their application in medical field. However, manuscripts without clearly describing methodologies would be eliminated during the manuscript selection. We obtained some research papers from the selected manuscripts’ reference list. The selected manuscripts and corresponding references were stored in EndNote. In total, 1 book section, 4 journal articles and 9 conference proceeding papers that discussed the colour correction method in conventional usage. Meanwhile, 2 journal articles and 1 conference proceeding paper discussed the colour correction on dermoscopic images, while 6 journal articles and 6 conference proceeding papers discussed the colour correction on tongue images and 2 journal articles discussed the colour correction in telemedicine. Most of the research works were published during the last 10 years, mainly due to the usage of colour images in the medical field for diagnosis.

3. IMAGE FORMATION

Image formation involves the interaction of illumination, material reflection, and observation processes. When light is emitted and interacts with materials, it results in reflection, absorption, and modulation of light intensity, depending on the material’s properties, and is finally recorded by the camera. Reflection models are models that describe the interaction between the three processes and simplify certain aspects of the process. Two common reflection models, the Lambertian reflection model and the dichromatic reflection model, are briefly described in this section.

As described in previous studies, the Lambertian reflection model assumes the intensity of the light reflected by the surface is independent of the viewing angle (2, 3). The matte material interacts with light and results in isotropic surface luminance. Based on the Lambertian reflection model, the colour image *I* at every pixel *(x, y)* can be expressed as the product of illuminant *(e)*, surface reflectance *(s)*, and camera sensitivity *(ρ)* which is represented in Equation 1, where λ denotes spectral wavelength over the visible spectrum. Assuming that the illuminant *(e)* is always uniform in the whole scene, the equation can be simplified as Equation 2. The final equation is represented in Equation 3:

$$I(x,y) = \int_{\lambda} e(x,y,\lambda)s(x,y,\lambda)\,\rho(\lambda)\,\delta\lambda \tag{1}$$

$$e = e(x,y) = \int_{\lambda} e(x,y,\lambda)\,\rho(\lambda)\,\delta\lambda \tag{2}$$

$$I(x,y) = s(s,y) \circ e \tag{3}$$

Another type of reflection model is called the dichromatic reflection model (DRM). This model emphasises the colour aspects of light reflection and has only limited usage for geometry recovery of scenes. It assumes a single light source in the scene, and this model includes Fresnel reflection (highlights), which the Lambertian model neglects. Hence, this model is suitable for the class of inhomogeneous materials. Colour image *I* at every pixel *(x, y)* based on the DRM model can be expressed as the summation of body reflectance (superscript *b*) and the interface reflectance (superscript *i*) respectively. The original formulation of the DRM is expressed in Equation 4:

$$I(x,y) = m^b(x)\int_{\lambda} s(\lambda,x,y)\,e(\lambda)\,\rho(\lambda)\;d\lambda + m^i(x)\int_{\lambda} s(\lambda,x,y)\,e(\lambda)\,\rho(\lambda)\;d\lambda \tag{4}$$

4. COLOUR CORRECTION FOR COLOUR CONSTANCY

Colour correction for colour constancy in images is defined as the process of altering the overall colour of the image to account for different lighting conditions. The objective of this process is to mimic the human visual system's ability to perceive the colour of the object appearing regardless of the varying illumination. In other words, this approach is to ensure the object appears its natural colour regardless of the photograph being taken under different lighting conditions. This section will split into two subtopics to discuss the colour correction method application for conventional usage and the medical field.

4.1 SIDs Conventional Colour Correction Method

The popular techniques used for colour constancy colour correction are mainly categorised into four types, which are statistical-based colour correction methods, least square approximation colour correction methods, gamut-based learning methods, and learning-based colour correction methods. Each of the colour correction methods will be discussed in detail.

4.1.1 Statistical-based Colour Correction Method

Statistical-based colour correction methods achieve colour constancy based on the correlation between illumination and surface reflectance. Some of the well-known statistical-based colour correction methods are Grey World, max-RGB, Shade-of-Grey and Grey-edge Hypothesis. The Grey-World method estimates the illuminant by computing the average value of all pixels, assuming that the colour of the object is achromatic and uniformly distributed over the entire colour image (13, 14). However, the colour correction accuracy will be impacted when a dominant colour is present in the image. To overcome this limitation, Li and Wu optimised the Grey-World algorithm by proposing a saliency detection. With this optimisation, the background with a more dominant colour will be removed, and only the foreground part with more colour variation will be used for illumination estimation calculations (15). The max-RGB or White-Patch approach computes the maximum responses in three colour channels, as it assumes that the maximum response in an image corresponds to perfect reflection (16). Shades-of-Grey is an extension of the Grey-World and max-RGB algorithms. By introducing the Minkowski norm, pixels with higher intensity are given a higher weight to normalise and compute the estimated illumination vector (17). The Grey-Edge hypothesis claims that the average of the reflectance differences in a scene is achromatic. The Grey-Edge hypothesis can be computed through Equation 5.

$$e_c = k\left(\int\left|\frac{\partial^n c^\sigma(x)}{\partial x^n}\right|^p dx\right)^{\frac{1}{p}} \tag{5}$$

Based on Equation 5, $c^\sigma(x)$ represented image that was captured by the camera, e_c is the estimated lightning and k acts as a scaling factor that varies according to the scene observed. Colour constancy based on Equation 5 indicates that the p-th Minkowski norm of the n-th order derivative in a scene is achromatic.

4.1.2 Least Square Approximation Colour Correction Method

Least square approximation colour correction method that categories use full matrix transformation using the least square algorithm to correct colour inaccuracies in the image. The colour correction matrix is calculated by comparing the colour values of a reference image, for instance, the ColorChecker matrix, with its known ideal colour values. The least squares algorithm then finds the optimal matrix that minimises the overall difference between the measured and ideal colour. The equation of the least squares approximation is expressed as below:

$$(C'_1, C'_2, \ldots, C'_{n)}, = T \bullet (C_1, C_2, \ldots, C_n) \tag{6}$$

$C'i$ and Ci $(i = 1, \ldots, n)$ are the colours from two different cameras and T is the transformation matrix between them. Given a set of corresponding colours from two cameras, the transformation matrix T can be computed by least square approximation. The transformation matrix is used for colour correction purposes. This method also includes linear least square approximation and polynomial least square approximation.

This least square approximation method can be further extended to linear and polynomial regression. Linear regression is to show the linear relationship between the independent and dependent variables by finding the best line that minimises the differences between predicted and actual values. While polynomial regression shows the non-linear relationship between the independent and dependent variables, both variables are modelled as nth-degree polynomials.

In the past, the colour correction relied on the white point or achromatic information to correct the colour. In 2015, Cheng *et al*. (18) extended the potential of the white balancing by proposing a multi-colour balancing colour correction. This method makes use of each target chromatic colour to compute a 3x3 colour correction matrix, and this mapping is able to compensate for the impact of the lightning variation. However, the more the target colour is used, the more the complexity of the algorithm. To tackle this problem, (19) suggested only using three colours as target colours to calibrate the image. Three-colour balancing colour correction is proven to improve the colour correction accuracy as well as enhance the computational efficiency.

4.1.3 Gamut-based Colour Correction Method

Gamut-based colour correction methods assume that only a limited number of colours can be observed under certain illuminations (20). In other words, colour variation in the image is caused by deviations in the light source. The first phase of the algorithm involves finding a limited set of colours, called the canonical gamut, by observing different surfaces under a specific light source. After that, a set of feasible diagonal mappings is generated by mapping each gamut of the input images to the canonical gamut. One of the feasible mappings is selected and applied to the canonical gamut to obtain an estimated unknown illumination. This method is complex, and if the algorithm fails to accurately intersect several convex polyhedral, it will return a null solution. Many studies have attempted to overcome this limitation. Finlayson *et al.* (21) presented a simple yet efficient illuminant estimation method by classifying the image based on the consistency of plausible light and the gamut of the images. Arjan *et al.* (22) improved the robustness of illuminant estimation by utilising higher-order statistics (derivatives) and adjusting the offset of the image values. Cubical Gamut Mapping (CGM), introduced by Mosny and Funt, represented the colour gamut with a cube rather than a convex hull and improved the pre-processing and training phases of the gamut-based colour correction method. This successfully minimised the angular and RMS errors in illuminant estimation (22, 23).

4.1.4 Learning-based Colour Correction Method

These methods estimate illumination through iterative learning from a large number of training datasets. By extracting the intrinsic properties of the images as features, learning-based colour correction methods can study the complex relationship between these features and illumination. This section presents a review of recent literature on learning-based colour correction methods.

Xiong and Funt applied Support Vector Regression (SVR) to estimate the chromaticity of light illuminating a scene from the colour histogram of an image of the scene (24). Xu *et al*. (25) introduced the Illumination-Guided Triplet Network (IGTN), which uses a deep metric learning approach to overcome sensitivity to variations in image content. The IGTN generates Illumination Consistent and Discriminative Features (ICDF), which can categorise the image based on the types of illumination present, leading to robust illumination colour estimations. A Bayesian method was proposed by Daniel *et al*. (13) to resolve the colour constancy ambiguity using a multi-hypothesis strategy. Mahmoud Afifi *et al*. (26) proposed a k-nearest neighbour (KNN) strategy for colour correction. A nonlinear colour correction matrix that maps the incorrect image's colour to the target ground truth image's colour is computed. Based on the matrix, the authors use KNN to search the images with similar colour distributions and use the corresponding colour correction matrices to correct the input images. They also proposed another Auto White Balance (AWB) method capable of handling both single and mixed-illuminant scenes. This method utilises a Deep Learning Neural Network (DNN) to learn suitable pixel-wise blending maps to correct for different lighting conditions in captured scenes and generate the final sRGB image (27).

Traditional colour correction methods often utilise the global colour enhancement methods to correct all pixels in the image. The drawbacks of this technique are high dependency on the global statistics and neglecting the local colour information. Hence, Wang *et al.* (28) proposed a local colour distribution model by dividing an image into small patches and the colour distribution of each patch was computed. The colour adjustment on brightness, contrast and colour balance is based on the local colour distribution while preserving local structure. This method is computationally efficient and suitable to implement in real-time processing applications. To conclude, Table 1 summarises the principles, strengths and limitations of statistical-based, least squares approximation, gamut-based, and learning-based colour correction methods.

Table 1. Comparison of conventional colour correction methods in SIDs.

Method	Principle	Examples	Strengths	Limitations
Statistical Based	Assuming scene statistics (e.g. average colour) can infer illumination.	• Grey World • Max-RGB • Shades-of-Grey • Grey-Edge	Simple, fast, no reference required	Fails in scenes with dominant colour, assumes ideal scene distribution
Least Squares Approximation	Finds transformation matrix using regression between reference and input.	• Linear / Polynomial Regression • Root Polynomial Regression	High accuracy, Supports polynomial expansion	Requires known reference colour, sensitive to input variations
Gamut-Based	Assumes limited colour gamut per illumination; maps to canonical gamut.	• Canonical / Cubical Gamut Mapping	Captures colour structure, models illumination diversity	Complex mapping, high computational cost
Learning-Based	Learn complex feature-illumination relationships from data.	• SVR • KNN • DNN	High adaptability in real-world scenes,	Requires annotated datasets, high computational cost

4.2 SIDs Colour Correction Method in Medical Field

True colour medical photography requires accurate colour representation for conveying accurate information to the clinician in diagnosis. Many existing studies in broader literature have examined the possibility of implementing colour correction in medical fields to fix inaccurate colour casts on true colour medical photography. Several SIDs colour constancy algorithms implemented in the medical field have been summarised in this section, which are telemedicine, medical facial and tongue colour in TCM and dermatology.

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4.2.1 Telemedicine

The demand for telemedicine or smartphone home-monitoring applications is rising. However, the smartphone camera-based health monitoring application may introduce colour distortion. To overcome this problem, (29) introduced a colour calibration technique that utilised the ColorChecker as a reference to calibrate the images using the least square estimation based colour correction method. The authors compare the absolute difference of the uncorrected and corrected colour value from the images captured by two different smartphone cameras and conclude that fewer colour intensity errors are observed in the colour-corrected image.

Takahashi *et al.* (30, 31) proposed an accurate colour examination approach to enhance the colour quality in telemedicine systems. A colour chart that includes the skin and tongue colour was created by the medical doctors and is used as a reference to carry out colour reproduction. The patient needs to capture their face and colour chart in the same image. Based on the picture, the colour transformation function algorithm is able to produce a transformation matrix to calibrate the colour discrepancies. A similar transformation matrix will be applied to the subsequent image. By integrating the colour chart into the diagnosis system, the authors conclude that this method improved the colour accuracy in the image and enhanced the reliability of diagnoses based on the visual information received through telemedicine platforms. Table 2 summarizes the methodologies and key findings of the colour correction studies in telemedicine contexts.

Table 2. Summary of colour correction methods for telemedicine applications.

Authors	Methods	Descriptions	Key Findings
Dang *et al*. (29)	Least Squares Approximation	Used ColorChecker and least square estimation-based colour correction	Reduced colour intensity errors between images from different smartphones after colour correction
Takahashi *et al*. (30, 31)	Least Squares Approximation	Used a custom colour chart (with skin and tongue colour) and applied transformation matrix based on image with patient's face and chart	Improved image colour accuracy and enhanced diagnosis reliability through consistent colour reproduction

4.2.2 Traditional Chinese Medicine – Tongue and Facial Image

To improve the colour accuracy of tongue digital images, Guojiang *et al*. (32) introduced an efficient approach to calibrate the colour distortion in tongue images. First, tongue images need to reduce their dimension to 3.6% of their original size to accelerate the image analysis process. After dimension reduction, the Grey World method is applied for colour correction. The proposed method offers rapid and effective solutions for correcting colour distortions in tongue images to provide a more reliable TCM diagnosis outcome.

Yan *et al*. (33) established a special colour target for tongue images to correct the colour response of the digital imaging device. A one-dimensional lookup table is created for each monochromatic channel (R, G, B) to align grey blocks in the colour correction target from the device's RGB values to the standard sRGB values. After the initial transformation, a colour correction matrix is applied to tongue imaging devices to calibrate the colour to the sRGB colour space to produce accurate colour representation. This proposed method was evaluated with perceptual colour difference: CIEDE2000 using 30 test colour images obtained from two different devices. The devices yield average and maximum values of 1.14 and 3.23 respectively, which satisfies the colour correction accuracy requirements for tongue imaging in TCM.

Wang *et al*. (34) introduced a computer-aided tongue diagnosis system that utilised a target-based method to calibrate the tongue image using a polynomial regression algorithm. As the authors stated, the Munsell ColorChecker was chosen as the reference target for colour calibration. The tongue image and Munsell ColorChecker need to be captured together in one image for colour calibration. The authors divide the ColorChecker patches into tongue-related patches and tongue-unrelated patches. Tongue-related patches are assigned a higher evaluation weight to calculate the colour difference between the images. The RGB values of the ColorChecker from the two images are extracted and input into the colour correction training algorithm. The polynomial colour correction can be described by Equations 7–9.

$$p_1, 3 = [R, G, B]^T \tag{7}$$

$$p_{2,3} = \left[R, G, B,\ R^2, G^2, B^2, RG, GB, RB\right]^T \tag{8}$$

$$p_{3,3} = \left[R, G, B,\ R^2, G^2, B^2, RG, GB, RB,\ R^3, G^3, B^3, RG^2, GB^2,\ RB^2, GR^2, BG^2, BR^2, RGB\right]^T \tag{9}$$

Jiayun *et al.* (35) suggested a colour correction method based on root polynomial regression. The purpose of this research is to improve the colour correction accuracy of the conventional polynomial colour correction method when illumination conditions change over time. The authors deployed a Root-Polynomial Colour Correction (RPCC) method to overcome the drawbacks of the traditional polynomial regression colour correction method. They explained that the conventional polynomial regression method is highly dependent on changes in illumination. When illumination changes, the R, G, and B components of each pixel in the image change linearly with the variation in illumination conditions. Unlike the conventional polynomial regression colour correction method, which is easily influenced by the light source, the proposed Root-Polynomial Colour Correction (RPCC) method can avoid the nonlinear variation in the image caused by changes in illumination conditions. Furthermore, RPCC is more concise compared to the conventional polynomial regression algorithm because it has fewer terms, as shown in Equations 10 and 11.

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$$\bar{p}_{2,3}=\left[R,G,B,\sqrt{RG},\sqrt{GB},\sqrt{RB}\right]^T \tag{10}$$

$$p_{3,3}=\left[R,G,B,\sqrt{RG},\sqrt{GB},\sqrt{RB},\sqrt[3]{RG^2},\sqrt[3]{GB^2},\sqrt[3]{RB^2},\sqrt[3]{GR^2},\sqrt[3]{BG^2},\sqrt[3]{BR^2},\sqrt[3]{RGB}\right]^T \tag{11}$$

The authors evaluated the performance of the RPCC algorithm using the CIE Lab colour space. Based on their results shown, this method appears to reproduce more robust and accurate colour correction under different illumination conditions. Zhang *et al.* (36) and Zhang *et al.* (37) introduced a tongue colour correction method based on the Support Vector Regression (SVR) algorithm. The authors first established a statistical tongue colour gamut based on the tongue image database to develop a novel Tongue Colour Rendition Chart. The newly developed Tongue Colour Rendition Chart worked with SVR to find the optimal hyperplane that can separate data points into different classes in the feature space. SVR algorithm adopted a nonlinear Support Vector Machine (SVM) dual formula by Vladimir Vapnik to transform the input data into a higher-dimensional feature space through the Gaussian kernel function. The final SVR function is given by Equation 12:

$$f(x) = \sum_{n=1}^{N}\left(a_n - \bar{a}_n\right)G\left(x_n, x\right) + b \tag{12}$$

The KKT complementarity conditions are:

$$\forall n : a_n(\varepsilon + \xi_n - y_n + f(x_n)) = 0 \tag{13}$$

$$\forall n : \bar{a}_n\left(\varepsilon + \xi_n - y_n + f\left(x_n\right)\right) = 0 \tag{14}$$

$$\forall n : \xi_n(C - a_n) = 0 \tag{15}$$

$$\forall n : \bar{\xi}_n(C - a_n) = 0 \tag{16}$$

The Lab values of calibrated image obtained by SVR based colour calibration model are given by Equations 17–18:

$$L^i_{oth} = f_L(L^i_{oth}, a^i_{oth}, b^i_{oth}) \tag{17}$$

$$a^i_{oth} = f_a(L^i_{oth}, a^i_{oth}, b^i_{oth}) \tag{18}$$

$$b_{oth}{}^i = f_b(L_{oth}{}^i, a_{oth}{}^i, b_{oth}{}^i) \tag{19}$$

Wei *et al*. (38) adopted Partial Least Squares Regression (PLSR) to calibrate the tongue images in the RGB colour space. PLSR is a robust statistical method that combines the characteristics of Principal Component Analysis (PCA) and canonical correlation analysis, making it capable of handling complex multiple regression problems. However, linear PLSR does not support device-independent colour spaces such as CIELAB. To overcome this limitation, Rosipal and Trejo (39) introduced a nonlinear kernel function into PLSR, transforming it from a linear method to a nonlinear one, resulting in K-PLSR. K-PLSR was adopted by Zhuo *et al.* (40) for TCM colour correction purposes, where the corrected tongue image can be obtained according to Equation 20:

$$\hat{Y} = \phi B = KU(T^T KU)^{-1}T^T Y = TT^T Y \tag{20}$$

where $\hat{Y}$ is the predicted result, ϕ is the matrix of training data mapped into the feature space. *B* is regression coefficient matrix while *K* is Gram matrix obtained. *U* and *T* represent the dependent and independent variable spaces, respectively. The authors utilised the Munsell ColorChecker as both the input and output to train the model, and this method successfully reduced the colour difference of each colour patch, providing excellent colour correction performance.

Another method proposed by Lu *et al.* (41) is the Two-phase Deep Colour Correction Network (TDCCN) for TCM tongue images. This methodology is divided into two phases. The first phase consists of an objective colour correction (OOC) network, which is capable of correcting the captured tongue image to standard lighting conditions with the presence of a ColorChecker. The input to the OOC network is a ColorChecker with 140 colour patterns to achieve a wider colour gamut. Three convolutional layers with a ReLU activation function in the OOC network transform the image from the spatial domain to the feature domain for feature extraction, ultimately generating the standard chroma value of the ColorChecker. The second phase consists of a flexible colour-adjusting scheme for perceptual colour correction, using the colour transfer method between images proposed by Reinhard *et al*. (42). The source image is first converted into the CIELAB colour space, then the ratio of standard deviations of the image is computed to normalise and scale the data in each channel using Equations 21–23.

$$l = \lambda_1\left(l_{in} - \mu_{l\,in}\right) + \mu_{l\,in} \tag{21}$$

$$\alpha = \lambda_2\left(\alpha_{in} - \mu_{\alpha\,in}\right) + \mu_{\alpha\,in} \tag{22}$$

$$\beta = \lambda_3(\beta_{in} - \mu_{\beta\,in}) + \mu_{\beta\,in} \tag{23}$$

where λ_1, λ_2, and λ_3 are user adjustment parameters. l_{in}, α_{in}, and β_{in} are the values of the input colour in $l\alpha\beta$ space, $\mu_{l\ in}$, $\mu_{\alpha\ in}$, and $\mu_{\beta\ in}$ are averages for each channel. This work successfully reduces the average colour difference under different lighting conditions, cameras and capture devices.

Hu *et al*. (43) presented an automatic tongue diagnosis framework to analyse tongue images taken by smartphones. The authors analysed existing colour correction methods for tongue images and found that most of them required a ColorChecker as a reference for colour correction. Therefore, the authors employed the double exposure theory to predict the lighting conditions. This framework also introduced a complete guide for the tongue photo acquisition procedure using smartphones. Only the pixels of the tongue colour in the current images, whose ratio falls within the range of [0.5, 0.8], are captured and further processed. Two tongue images: one captured with flash and the other captured without flash, are transformed from sRGB to CIExyY colour space. The colour values of the CIExyY colour space are used to compute the imposed intensity vectors for each colour channel, as shown in Equations 24–27.

$$C_1=(x_1,y_1),\ C_2=(x_2,y_2) \tag{24}$$

$$C'_1=(x'_1,y'_1),\ C'_2=(x'_2,y'_2) \tag{25}$$

$$x'_1-x_1\approx x'_2-x_2\approx f_x \tag{26}$$

$$y'_1-y_1\approx y'_2-y_2\approx f_y \tag{27}$$

where x_1, y_1 *and* x_2, y_2 are the two pairs of the chromaticity colour coordinates in the CIExyY colour space obtained under the lightning environment, x'_1, y'_1 and x'_2, y'_2 are another two chromaticity colours obtained by using the camera's flash to recapture these two pixels under the same lightning environment. The imposed intensity vectors (f_x, f_y) would be different if the images were captured under different lighting environments. SVM was implemented to predict the lightning condition and compute the corresponding colour correction matrix according to the colour difference of images taken with and without flash.

Previous researchers created the Simulated Annealing–Genetic Algorithm–Back Propagation (SA-GA-BP), a neural network-based colour correction algorithm to calibrate the colour of tongue images. Conventional Back Propagation (BP) uses the gradient descent (GD) algorithm in learning to minimise the squared error in the network (14). However, it often suffers from a low convergence rate due to sensitivity to weight initialisation and a high probability of getting trapped in local extrema. To overcome these issues, the authors adopted Simulated Annealing (SA) and the Genetic Algorithm (GA) to optimise the traditional BP neural network, where GA helps to find the global optimum, while SA optimises the initial weights of the BP neural network. Their results show that the SA-GA-BP colour correction algorithm improves colour accuracy with less computational complexity compared to whole-gamut colour correction algorithms, given ColorCheckers as input to train the neural network.

In Zhang *et al.* (44), the authors' colour correction approach is also based on back propagation (BP). To optimise the BP neural network, the authors introduced the MEC-BP-AdaBoost neural network-based colour correction method that adopted Mind Evolutionary Computation (MEC) to compute the initial weights and thresholds. The AdaBoost algorithm was used to train and form a new strong predictor. A total of 1020 RGB values from ColorCheckers were used for training. The authors compared the proposed method with other colour correction methods, such as the polynomial regression model, the conventional BP neural network, and the genetic algorithm (GA)-BP neural network, and concluded that the proposed method offers higher colour correction accuracy.

Another group of authors proposed the Tongue Colour Correction Generative Adversarial Network (TCCGAN) to address colour discrepancies in tongue images using a stack GAN architecture (45). The authors present a differentiable weighted histogram network to extract colour features from images, which were in then used in mixed feature attention upsample module to assist image generation. The stack GAN networks were designed to produce corrected tongue images. Experimental results demonstrated that the proposed TCCGAN generated high-quality corrected tongue, that helps in downstream diagnosis and classification tasks.

Facial images also play an important role in TCM for diagnosis purposes. Hence, Niu *et al.* (5) proposed an optimised colour correction scheme for medical facial images. A total of 122 undistorted facial images are used for analysis and define a complexion gamut that provides a precise range of skin tones. Based on the complexion gamut, the authors identify the optimal colour patches that are crucial for effective colour correction. There are three colour correction methods: polynomial regression, SVR and ANN, tested in this study to find out the most effective colour correction algorithm. The author proved that polynomial regression with a polynomial term of 13 gave the optimal colour correction result compared to other methods by achieving a colour difference of 1.55.

In Hemrit *et al.* (46), instead of using the least square approximation method for colour correction, the authors use the Monge-Kantorovitch (MK) transport function to achieve colour constancy in the Kampo pathophysiology diagnosis. The advantage of using the MK transport function is that colour correction can be carried out without image registration. Based on this transform function, the colour in an image and reference are treated as a probability distribution in a multi-dimensional colour space. Based on the two-colour distributions (ground truth image and input medical image), it is able to compute the optimal colour mapping function that minimises the transport cost between the input and reference colour distributions. The authors proved that the colour correction performance based on the MK transform function is better than the least squares regression method. Table 3 summarizes the colour correction studies and their key findings in TCM applications.

Table 3. Summary of colour correction methods for TCM applications.

Authors	Methods	Descriptions	Key Findings
Guojiang *et al*. (32)	Statistical based	Apply Grey World method for colour correction	Fast and effective correction; improved reliability for TCM diagnosis
Yan *et al*. (33)	Least Squares Approximation	Alignment of device RGB values with standard sRGB values using a lookup table.	High accuracy with CIEDE2000: Avg 1.14, Max 3.23;
Wang *et al*. (34)	Least Squares Approximation	Polynomial regression with Munsell ColorChecker; weight assigned to tongue-related patches	Improved colour accuracy compared to traditional methods under varying illumination.
Jiayun *et al*. (35)	Least Squares Approximation	Root-Polynomial Colour Correction (RPCC) to improve over traditional polynomial correction	More robust and accurate under different lighting
Zhang *et al*. (36, 37)	Least Squares Approximation and Learning-based	Support Vector Regression (SVR) using custom Tongue Colour Rendition Chart	Non-linear correction using SVM duality principles
Wei *et al*. (38), Rosipal and Trejo (39), Zhuo *et al*. (40)	Least Squares Approximation	Used PLSR and introduced K-PLSR (nonlinear kernelized version) for device-independent spaces	Achieved high colour accuracy by reducing colour differences in tongue images, especially with nonlinear kernel functions (K-PLSR).
Lu *et al*. (41)	Learning-based	TDCCN (Two-phase Deep Colour Correction Network): OOC + Perceptual colour adjustment	Robust under diverse capture conditions; deep learning enhances perceptual correction
Hu and Cheng *et al*. (43)	Learning-based	Using double exposure theory combined with SVM to predict lighting and generate colour correction matrix	Enables chart-free correction using CIExyY colour space and intensity vector calculations
Zhuo *et al*. (14)	Learning-based	Hybrid SA-GA-BP neural network uses Simulated Annealing + Genetic Algorithm to optimize BP	Outperformed full-gamut correction with lower complexity
Zhang *et al*. (44)	Learning-based	MEC-BP-AdaBoost neural network using Mind Evolutionary Computation and boosting strategy	Superior to BP, GA-BP and polynomial regression; high accuracy
Yan *et al*. (45)	Learning-based	Proposed TCCGAN, a stack GAN with histogram-based colour features and mixed attention module	Generated high-quality corrected tongue images and improves downstream tasks
Niu *et al*. (5)	Least Squares Approximation and Learning-based	Using polynomial regression, SVR, and ANN for colour correction based on facial skin tone gamut	Polynomial regression (13th order) achieved lowest error (1.55 ΔE)
Hamrit *et al*. (46)	Least Squares Approximation	Used Monge-Kantorovitch (MK) transport function for colour constancy	MK-based method outperformed least square and doesn't require registration

4.2.3 Dermatology

Dermoscopic images are useful in diagnosing skin cancer with the aid of several Computer-Aided Diagnosis (CAD) systems. However, most of the dermoscopic image datasets used for analysis are obtained through specific acquisition devices and illumination conditions. Instead of adjusting or standardising the dermoscopic image acquisition setup, Barata *et al.* (47) utilised the Shades-of-Grey method for colour calibration before performing lesion classification to improve the performance of the diagnostic results. These studies demonstrate the essential need for colour constancy algorithms by comparing the performance of skin classification with corrected and non-corrected dermoscopic images from heterogeneous datasets.

Nowak *et al.* (48) proposed a colour calibration model for skin lesion images by categorising the images into four groups: standard, white (overexposed images), pink (incorrect red balance), and blue (incorrect blue colour balance), based on their colourimetric characteristics. The "standard" group is used to calculate the base model. For images in the other groups, the colour pixel occurrence rate is computed and mapped into a 4D histogram. The two points (the darkest point and the highest occurrence pixel point) are selected to manipulate the distribution of the colour model using linear transformation. The performance of the colour calibration result is verified by calculating the Total Dermoscopic Score (TDS) coefficient of the ABCD rule:

$$TDS = A*1{,}3 + b*0{,}1 + C*0{,}5 + D*0{,}5 \tag{28}$$

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where A, B, C and D values correspond to different features of the skin lesion. A – asymmetry; B – border; C – colour (red, blue-gray, brown, black, white); D – dermoscopic structures

DermoCC-GAN (Dermatological Colour Constancy Generative Adversarial Network) was developed to perform a colour constancy task on dermoscopic images (49). Traditionally, dermoscopic images employed statistical-based colour constancy methods. However, due to the limitations of statistic-based assumptions, these methods often result in suboptimal colour constancy normalisation. DermoCC-GAN combines two deep neural networks, which serve as the generator and discriminator, respectively. The training phase is terminated when the generator successfully fools the discriminator into generating realistic and accurate images. By evaluating the impact of colour constancy from the clinical dermatologist's perspective, the authors concluded that this deep network was able to perform the colour constancy task on skin lesion images quickly and efficiently, even under different illumination conditions.

Santos *et al.* (50) emphasize the importance of lighting and colour in classifying malignant skin cancer using deep neural network architectures by comparing the performance of deep learning classification models with and without undergoing colour correction. By applying conventional colour correction techniques such as Local Colour Distribution Prior Network (LCDPNet) (28), Low-Light Neural Radiance Field (LLNeRF) (51), and deep symmetric network (DSN) (52), the precision of the classification improves between 3 to 4%. Among these three-colour correction techniques, the LCDPNet and LLNeRF techniques showed improvements in most classification metrics. Table 4 summarizes the colour correction studies and their key findings in dermatology applications.

Table 4. Summary of colour correction methods for dermatology applications.

Authors	Methods	Descriptions	Key Findings
Barata *et al.* (47)	Statistical based	Applied Shades-of-Grey colour constancy method before lesion classification	Improved skin lesion classification accuracy on heterogeneous datasets
Nowak *et al.* (48)	Statistical based	Classifies images into groups based on histogram for tailored colour calibration.	Colour calibration validated using Total Dermoscopic Score (TDS) of the ABCD rule
Salvi *et al.* (49)	Learning-based	Proposed GAN-based colour constancy method with generator and discriminator for accurate image normalization	Achieved realistic colour correction; robust across lighting variations
Santos *et al.* (50)	Learning-based	Compared DNN classification with and without colour correction using multiple deep correction models: LCDPNet, LLNeRF and DSN	Colour correction improved classification accuracy by 3–4%

5. DISCUSSION

All the methods discussed in Section 4 have made significant contributions over the years. Specifically, each method has its own pros and cons for implementation, as well as certain problems and limitations. In this section, we will discuss and provide our thoughts on all the methods in an unbiased manner. Statistical-based colour correction methods rely on the low-level features of the image for illumination estimation. The colour gamut of the image is first converted to a specific colour space, and the chromatic components are mapped into a 2-dimensional colour histogram, with the lightness component separated. Through statistical analysis of the histogram, statistical-based colour correction methods can distinguish between the true colour cast and the predominant colour appearing in the image. These methods are simple and yet effective, which are widely used for colour normalisation or image enhancement in conventional usage as well as in the medical field (32, 47, 48). However, it is advised to select statistical-based colour correction methods wisely before implementation because some of the algorithms, such as Grey-World algorithms, tend to produce inaccurate results when a dominant colour is present in the image. Due to these factors, attempting to replicate the Grey-World algorithm for medical applications, such as tongue or skin close-up images, might lead to suboptimal or false results due to the dominant colour present.

Partial least squares, polynomial, and root-polynomial regression are categorised under least square based approximation colour correction methods. These methods correct the colour of images by computing the regression coefficients based on reference ColorChecker charts. Continuous variables and transformation degrees in the regression algorithm provide flexible optimisation while maintaining low execution time, which encourages the researcher to implement these techniques in their works (33-35, 38, 39, 46). To further enhance the colour correction performance of the least square based approximation colour correction methods, many researchers established a new colour chart based on the targeted colour gamut (30, 31, 33) or applied more weight on specific colour patches that highly relate to the target colour gamut (34). There are also some hybrid approaches (40, 44) that combine the benefits of regression and neural networks to achieve better colour correction performance.

With the development of machine learning, more versatile, optimised, robust, and faster algorithms have been introduced for colour constancy tasks. In recent years, the rise of machine learning has significantly contributed to the field of learning-based colour correction methods. Techniques such as SVM, CNN, and many others have been implemented for colour correction in medical images. Many researchers use the value of the ColorChecker chart as input to train machine learning models (5, 14, 41, 44, 50), except for two previous studies which use the double exposure method to identify the colour cast for colour correction purposes (43, 46). However, such methods require several images paired with appropriate "ground truth" information to achieve satisfying predictions. Although learning-based colour correction methods can provide relatively realistic results, they require extensive human resources for data collection and labelling (26, 27, 45, 49, 53). Data collection can be challenging, especially in the medical field, because home-monitoring patients are not usually located within the hospital. Direct access to the equipment or ColorChecker charts may not be available for the patient to use when needed. Furthermore,

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correct data labelling is crucial for accurate colour correction results, particularly in supervised learning approaches. Data labelling must be done by medical experts, which can incur significant costs due to the need to hire many specialists. In short, while learning-based colour correction methods are more computationally complex and require more computational time, they generally provide better illumination estimation compared to statistical-based colour correction methods.

The common performance evaluation indicator for the colour correction methods discussed in the previous section is colour difference. This involves a comparison between the predicted or colour-corrected colourimetry with the target colourimetry and calculating the colour distance between them using proper evaluation metrics. Several evaluation metrics, such as mean angular error, perceptual colour difference (CIEDE2000 and CIE1976) and Euclidean distance, are used to report the overall performance of the colour correction algorithm. Most of the colour differences were computed based on ColorChecker chart (35, 36, 44) and only a few were computed based on ground truth images (53). However, the ColorChecker chart used to compute the colour difference may vary from one study to another in terms of the ColorChecker chart types and the targeted illumination. Moreover, some colour correction methods also evaluate algorithm performance in terms of execution time. Both performance evaluation approaches are considered objective evaluations and provide reliable results.

6. CONCLUSION

This study summarised the methodologies employed in smartphone-based medical image colour correction over the past decade. As highlighted throughout the paper, advancements in colour correction technology have made significant strides in recent years, and this technology has been successfully applied to the medical field. By improving or correcting medical images captured by SIDs, we can achieve higher colour reproducibility, which enables the generation of high-quality research data and provides valuable insights for medical diagnosis and treatment options.

From the contributions discussed in the previous section, learning-based colour correction approaches have produced promising results, particularly in mitigating the impact of light sources and reconstructing the true colour of objects. Given the growing popularity of learning-based methods, there is an increasing need for standardised ground truth datasets to facilitate the generation of reliable calibration results. While most existing methods yield excellent colour correction outcomes, they are not yet universally adopted by medical professionals or patients. This may be due to the specialised and often expensive equipment required to achieve accurate colour constancy. Furthermore, many learning-based colour correction algorithms in the medical field have been trained using datasets obtained from image acquisition devices under controlled lighting conditions, which may not fully represent the varied lighting environments encountered in real-world scenarios, such as in SID images taken under open lighting conditions.

For practical adoption of learning-based colour correction in medical application, future work should focus on real-world clinical images captured using SIDs under diverse lighting conditions. A critical step involves developing standardized benchmark or training datasets that incorporate reliable colour references such as Macbeth charts and are acquired under varied lighting conditions. These datasets can serve as training or evaluation material to help model generalization in clinical scenarios and improve the accuracy of colour correction in practice. Exploration of lightweight and mobile-friendly machine learning frameworks is crucial to enable real-time colour correction processing on smartphones without compromising accuracy. Integration of domain knowledge into deep learning frameworks for instance incorporating physical principles of colour formation could enhance robustness and generalisability of colour correction models.

In summary, while existing colour correction methods have shown encouraging results, their full potential in mobile medical applications can only be realised through the development of realistic datasets, open-environment validation, and the adoption of scalable, interpretable, and efficient learning frameworks. These steps will move the field closer to deliver practical and widely accessible solutions for colour-accurate smartphone-based diagnostics.

AUTHORSHIP CONTRIBUTION STATEMENT

Wee Li Low: data curation, resources, writing – original draft, formal analysis; Yuan Wen Hau: supervision, conceptualization, writing – review & editing; Chia Yee Ooi: supervision, conceptualization

DATA AVAILABILITY

Data are available within the article or its supplementary materials.

DECLARATION OF COMPETING INTEREST

The authors have no conflict of interest to declare that are relevant to the content of this study.

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