New Directions for Skincare Monitoring: an NFC-Based Battery-Free Approach Combined with Deep Learning Techniques

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ABSTRACT Skincare monitoring has always been of paramount importance in the field of dermatology. In this study, we developed a smart skincare device that can harvest energy from a near field communication (NFC)-based smartphone and allow the adoption of a battery-free design approach. This device consists of two integrated sensors: one for the measurement of skin moisture and another for that of ultraviolet (UV) radiations. We conducted a series of experimental tests on different subjects in indoor and outdoor environments (8 and 6, respectively). Their skin moisture and temperature were measured parallelly to the ultraviolet A (UVA) and ultraviolet B (UVB) radiations from the sun. Later, the 6 channel sensing outputs obtained from the sensors (including ambient humidity and temperature) were input into a deep learning artificial neural network (ANN) model, which was used to predict the corresponding outputs and calculate the respective mean square error (MSE). The ultraviolet index (UVI) outputs were classified (using the same ANN model) into “less harmful”, “moderate harmful” and “burn”. The overall classification accuracy was 99.8%: the best performance achieved by using an ANN model. Notably, our skincare device is enclosed in a 3D flexible design print and is smart, battery-free, equipped with an Android application interface and more convenient to transport than other commercially available devices.

INDEX TERMS Artificial neural network model, near field communication, skin moisture, skincare, UVI.

I. INTRODUCTION

HUMAN skin includes three main depending layers: the fatty subcutaneous (hypodermis) layer, the overlying dermis and the epidermis. Epidermis lies in the outermost layer of the skin and consists of an inner and an outer part. The outer part is known as the stratum corneum (SC) [1] (Fig. 1(a)). The SC regulates the skin moisture content level: failing to retain the desired moisture level might induce skin dryness or roughness.

Detecting the water content of the SC is very important in dermatological cosmetic research. Due to several detrimental factors (e.g., environmental changes), the SC may become unhealthy; this can result in a reduction of its efficiency as a barrier and in a considerable decrease of its moisture retaining factors. In this context, the maintenance of an adequate moisture level in the SC is of utmost importance. Our research stands to focus on the subjects, who are particularly
interested in their skin health and appearance. The humidity sensor is used to measure the corresponding skin moisture levels [2]. Several sophisticated commercial skin moisture devices (e.g., Novameter, Corneometer, Skicon-200) have been developed a decade ago and applied to the measurement of SC hydration [3]–[7]. Previously in dermatological research, majority of the work have been done to find out the behavior of skin moisture [8] using occlusion dressing, before and after removing, with the help of a device (Hygrometer RF-820). In another work, [9], a water bath method was developed to determine the dynamic response of the skin.

Several different methods and techniques (e.g., electrical, mechanical, microwave, thermal and spectroscopic) have been developed in cosmetic research for the measurement of skin moisture. In [10], authors used near infrared (NIR) system integrated with a photodiode array detector to measure skin moisture. Measurement techniques based on electrical method (include capacitance, impedance, conductance, and resistance) have been widely adopted in cosmetic research. For instance, a capacitance-based device (Corneometer CM 825) was used in [11]–[13] to compare skin moisture with tri-biological, physical, and physiological parameters.

Other parameters, e.g., ultraviolet (UV) radiations, which include UVA, UVB and UVC rays are also given vital importance in cosmetic dermatology. UV irradiations are less powerful than UVB radiations but can still cause several types of cancer; meanwhile, UVB radiations are highly energetic and can damage the DNA of skin cells [14]–[16]. In consideration of the aforementioned deleterious problems and in order to increase the level of protection, the World Health Organization (WHO) has already issued a standard known as the ultraviolet index (UVI) [17]. As reported in [18], some commercially available battery-based UVI devices (Netatmo June, Raymio, Microsoft’s Band 2) can be worn on the wrist of a user or attached on clothing, while others (Sun Sprite and L’Oréal’s My UV Patch, France) operate on solar power.

All of the skincare devices mentioned above have some demerits: 1) they need a battery or solar power to operate, 2) most of them are usually big and cannot be conveniently transported, 3) cannot be classified as smart and wearable devices.

The near field communication (NFC) technology was developed a decade ago [19], [20], but mostly applied to payment systems. NFC uses electromagnetic induction to enable the communication between devices located at a distance of a few centimeters (especially 2 cm) from each other and works on the 13.5 MHz ISM band [21]. NFC does not require the pairing of devices and represents a very convenient and efficient way of obtaining the data. However, NFC works only on the short range: the amount of data and harvested power can only be transmitted within a short distance range. Importantly, NFC-based sensors that use green harvested energy allow the design of smart wearable devices (i.e., man-machine interfaces) [22]. Such devices are becoming increasingly important and the latest smartphones contain NFC chips [23]–[25]. Interestingly, now the NFC-based smartphone can mitigate the problems involved in the replacement of sensor mote batteries.

Ambient energy sources like solar power (15 mW/cm² [26]), wind power (28.5 mW/cm² [26]), piezoelectricity (330 W/cm³ [26]), and thermoelectricity (20–60 W/cm² [27]) are all available options for energy harvesting [28]. In these cases, the harvested energy tends to be low and has to be stored in a battery, which needs a considerable amount of time to be completely charged [27]. Energy harvesting through NFC or RFID is considered a smart choice for embedded sensor system applications [29]–[31]. Recently TI-, AMS-, NXP-, and ST- Microelectronics have introduced several low-power integrated chips with enhanced data reading, writing, and storing capabilities [32]. In this paper, we present a smart skincare device with a novel design that can harvest energy from NFC-enabled Android smartphones.

Previously, many works have been done to exploit the benefits of NFC. For example, a NFC-WISP (NFC Wireless Identification and Sensing Platform) was developed to monitor cold chain applications through the E-ink screen [33]. The medical and biological science is already taking the advantage of NFC by using smart sensors that can monitor the health of patients and transmit the resulting data through a smartphone [34]–[38]. NFC has been employed in the latest smartphones and since 2018, is becoming increasingly important in the Internet of Things (IoT) industry because of its deployment in the latest smartphones. Since then researches tried to test the applicability of NFC to a number of battery-less applications like soil moisture measurements [39], fruit analysis [40], bicycle tire pressure [41], smart diaper [42], and pH monitoring [43].

The smart skincare device proposed in this study does not need any battery to operate; in fact, it depends only on the harvesting source which is the NFC smartphone. The energy is first harvested from the NFC-enabled smartphone and then provided to the sensors. Afterwards, all the information collected by the sensors is transmitted to the NFC smartphone through a NFC transponder chip. Then this sensing information from the NFC smartphone is passed to deep learning models to further apply signal processing techniques and make predictions on the outputs. Artificial neural network (ANN) models have been developed a long time ago [44], so in this manuscript, we utilized an ANN model with two hidden layers to process the 6 channel output obtained from the sensors, which was found to be robust and able to efficiently predict the corresponding outputs.

The rest of this manuscript is structured as follows:- Section II describes the overall structure of the system model, Section III describes the transmitting NFC smartphone antenna and the receiving skincare device antenna, Section IV provides information regarding to the developed Android application (app) and the energy harvesting performed by the skincare device, Section V provides the experimental results, Section VI introduces the deep learning mechanism used for output prediction and data classification, and section VII
summarizes our conclusions.

II. SYSTEM ARCHITECTURE

Figs. 2 shows the system structure diagram of the overall skincare device, which consisted of a circular designed NFC antenna that harvested energy from the NFC smartphone, a rectifying circuit, an NFC transponder chip, an ultra-low power microcontroller (MCU), a skin moisture sensor, and a UV detection sensor. The MCU could work at different clock speeds (typically 1 MHz) while consuming different amounts of power (1.8–2.2 V at 230 µA). The NFC chip complied with the ISO14443B standard and required only 250 µA at 400 kHz while writing an NFC data exchange format (NDEF) message. The skin moisture sensor required 1.8 µA at 1 Hz, when the humidity and temperature modes of the sensor were turned on, while the UV detection sensor required a current of 480 µA to operate. Table 1 shows that the current consumption of our skincare device was the lowest among those of devices presented in previous studies.

Our smart skincare device was fabricated on an FR4 substrate (Fig. 3), so that it could operate in a fully passive mode. The spiral coil antenna and the UV sensor were located at the top of the device, while the MCU, the NFC transponder, and the skin moisture sensor were located at the bottom so that they could easily receive the sensor readings (Figs. 3(a), (b)). The device, having a circular PCB (printed circuit board) shape with a diameter of 2.6 cm, was enclosed in a flexible 3D-printed object that was designed to give support to PCB and facilitate the collection of skin moisture and UV information from a particular subject (Fig. 3(c)).

III. ANALYSIS ON TRANSMITTING AND RECEIVING COILS

A. STRUCTURE OF THE NFC SMARTPHONE ANTENNA

The NFC coil is already embedded on the battery of smartphone. In our case, we chose a well-known smartphone (Samsung Note4, Korea) in experiment for the analysis of battery-free operation of the skincare device. The NFC reader of this smartphone is able to read a variety of communication standards, like ISO 14443A or ISO 15693 [43]. The inductance of coil is one of the key parameter to determine its performance. There are total 16 conductor segments in the rectangular coil of NFC smartphone having 4 full turn inductors (Fig. 4). In this figure, “s” indicates the spacing between each conductor loop, “w”, the width of each conductor segment, “δ = s + w”, the distance between two conductor segments of this rectangular loop and \( l_1, l_2, l_3, \ldots l_{16} \), the lengths of the rectangular conductor segments. According to [21], the self-inductance of one turn rectangular segment is given by:

\[
L = 0.002 \left\{ \ln \left( \frac{2l}{w + t} \right) + 0.50049 + \frac{w + t}{3l} \right\} \quad (1)
\]

where \( w \), \( t \), and \( l \) are the width (0.1), thickness (0.01), and length (x) of the segment, respectively (in cm).

The total self-inductance of the rectangular spiral loop is equal to the sum of the self-inductances of each straight-line conductor segment:

\[
L_{tot-self} = L_1 + L_2 + L_3 + \ldots + L_{16} = 0.617 \mu H \quad (2)
\]

Meanwhile, the total inductance of the rectangular coil is equal to the sum of the self-inductances of each conductor, plus all the mutual inductances between these conductors. The value of the total inductance in our case, calculated through mathematical analysis, was of 1.1 µH.

B. DESIGN OF THE ANTENNA FOR THE SKINCARE DEVICE

A well designed and fabricated antenna is necessary in order to allow the harvesting of sufficient energy through the
TABLE 1. Current Consumption by different Battery-Free NFC based Devices

| Components          | I(µA) | Refs [40], [43] | Components          | I(µA) | This paper |
|---------------------|-------|-----------------|---------------------|-------|------------|
| NFC (M24LR04E)      | 400   | NFC (M24LR04E)  | 400                 |       |            |
| MCU (ATtiny85)      | 300   | MCU (ATtiny85)  | 300                 |       |            |
| Humidity (HIH5030)  | 200   | Color (TCS34725)| 235                 |       |            |
| Temperature(LM75)   | 280   | LED             | 2000                |       |            |
| Timer(ICM555)       | 60    |                 |                     |       |            |
| **Total**           | 1240  |                 | 2935                |       | **961.8**  |

NFC-enabled smartphone. Hence, we designed an antenna that could work efficiently at a frequency of 13.5 MHz, and harvest the maximum possible energy from the NFC smartphone coil. The coupling between the NFC smartphone antenna and that designed for the skincare device was based on electromagnetic induction and depended on the tuning of the receiving antenna. We chose to employ a spiral wound antenna with 6 turns in order to harvest sufficient energy for powering up the rest of the circuit. The dimensions of the designed receiver antenna are shown in Fig. 5. The total self-inductance of the spiral wound coil is given by [21]:

$$L = \frac{(0.3937)(aN)^2}{8a + 11b} \mu\text{H}$$

(3)

wherein, $a = \frac{(r_i + r_o)}{2} (\text{cm})$, $b = r_o - r_i (\text{cm})$

In the above equations, $r_i$ and $r_o$ are the inner and outer radii, respectively, of the spiral coil (in cm), while N corresponds to the number of turns of the spiral coil. Notably, $r_1 = r_1 = 1 \text{ cm}$, $r_2 = 1.05 \text{ cm}$, $r_3 = 1.1 \text{ cm}$, $r_4 = 1.15 \text{ cm}$, $r_5 = 1.2 \text{ cm}$, $r_6 = r_o = 1.25 \text{ cm}$, $a = 1.125 \text{ cm}$, and $b = 0.25 \text{ cm}$. By inserting all these values in Eq. (3), we obtained the value of the total self-inductance of the receiver coil (1.52 $\mu\text{H}$). Since our skincare device is based on an energy harvesting mechanism, the maximum amount of current generated for the sensors and other peripherals depends on the magnetic field, and the coupling between the two coils. Since the components of similar devices require additional power, they are usually placed nearer to the smartphone compared to conventional NFC chips: in this way, the magnetic field effect is increased [22].

Fig. 6 illustrates the simulation results of the magnetic field intensity (H), energy transfer, and current density (J) between the transmitting and receiving coils on a well-known magnetic simulator (Ansoft Maxwell, Ansoft Corp., USA). These were obtained considering the exact lengths of the conductors and the distance between them (2 cm). Fig. 6(a) shows the H values calculated for the space between the NFC smartphone and the designed receiver coils on a scale comprised between 10.663–364.48 A/m. The figure suggests that, when the skincare device coil was placed closer to the NFC smartphone, the values of H between the two coils increased. Similarly, Fig. 6(b) illustrates that the distribution of energy is much more intense near to the NFC smartphone. As per simulated results from Fig. 6(b), the strongest energy that can be transferred to the receiver coil is 3.44 mJ/m$^3$. Finally, Fig. 6(c) demonstrates the homogeneous distribution of the current density (J) between the NFC smartphone and...
the skincare receiver coils (within the whole radiation box region): the green region corresponded to J values comprised between 4.71–92.51 mA/m². In conclusion, the device performance could be improved by moving its antenna as closer as possible to the smartphone.

IV. SYSTEM MODEL AT THE RECEIVER SIDE

A. ENERGY HARVESTED BY THE SKINCARE DEVICE FROM THE NFC-BASED SMARTPHONE

The energy harvesting efficiency depends on a number of factors, including the antenna dimensions. The maximum energy harvested from the NFC smartphone (Fig. 7) was measured using an oscilloscope (DSO7054A, Tektronix Inc., USA). The peak-peak ($P_{pk}$) voltage of the harvested energy was of 2.81 V when the smartphone was very close to the skincare device (~1 cm), but decreased when the smartphone was moved away from the skincare device antenna (>1 cm). Schottky diodes (CDBU0130L, Comchip Technology, China) were used during the rectification process in order to convert the harvested voltage into direct current (DC) voltage.

B. DATA COMMUNICATION BETWEEN THE COMPONENTS OF THE SKINCARE DEVICE

The MCU communicated with the NFC device and the two connected sensors through the I²C interface. After obtaining the data from the sensors, the MCU sent that information back to the NFC chip; then, the NFC chip sent the infor-
FIGURE 9. Android app used in combination with the skincare device: (a) main menu of the Android app (options for checking either skin moisture or UVI); (b) measurement of skin moisture through a battery-free NFC approach; (c) measurement of the UVI through a battery-free NFC approach; (d) half pie graph displaying the history of UVI measurements.

C. SMART ANDROID APP FOR SKINCARE SUPPORT

In the Android studio, the NFC skincare checkup app was developed for the monitoring of skin moisture and UV radiations. To control the two sensors data, three activities i.e., main activity, first activity and second activity were defined for proper operation of the app. Two separate options (rounded buttons) were deployed in the main activity of the Android app so that the subjects could select the desired choice of either skin moisture or UVI (Fig. 9(a)). For the experimental test, the smartphone was brought closer to the skincare device (∼ 1 cm). In our experimental testing, at first skin moisture was measured from a particular subject and when the smartphone took data from the skincare device, the Android interface was shifted to the second activity, where after taking the exact readings of the skin moisture using NFC smartphone app, a circular bar with the correspondent percentage values of the skin moisture were displayed. The maximum range of the circular bar was set to 100% (Figs. 9(a), (b)).

The same circular bar was used to display the UVI measurement; however, the maximum value was was set to a real index number of 11 (Fig.9(c)). Finally, the history of all the UVI measurements taken during the experiment was recorded and displayed in the form of a half-pie graph (Fig. 9(d)). Table 2 compares the characteristics of our skincare device with those of devices presented in the previous research. Our skincare device is the smallest among them and consequently provides one of the robust advantage that it works on a battery-free approach along with an interactive
TABLE 2. Comparison between different Devices used for the measurement of Skin Moisture

| Ref | Battery-Free | Type of Sensor | Device Dimensions (cm) | Sensor Size (mm) | Measurement          |
|-----|--------------|----------------|------------------------|------------------|----------------------|
| [1] | No           | Impedance      | 5 x 5 x 0.6            | 5 x 5 x 0.6      | TEWL                 |
| [2] | No           | Capacitance    |                        |                  | Skin Moisture        |
| [13]| No           | Capacitance    | 5 x 5 x 0.5            |                  | Skin Moisture        |
| [45]| No           | Capacitance    | 2.5 x 3.5              |                  | Skin Hydration       |
| [46]| No           | Resistance + Capacitance | 16 x 3 |               | Assessing Skin Properties Status |
| Our work | Yes          | Capacitance    | 2.6 (circular)         | 2.5 x 2.5 x 0.93 | Skin Moisture        |

FIGURE 10. Skin moisture on 8 subjects at different timings of the day during the indoor experiment.

Android user interface; these characteristics make it a convenient choice to use.

V. EXPERIMENTAL RESULTS

A. INDOOR AND OUTDOOR SKIN MOISTURE MEASUREMENTS

Skin moisture measurements were conducted on 8 subjects in an indoor environment and on 6 subjects in an outdoor environment at different timings of the day. For outdoor experimental testing, the subjects were asked to remain in the ambient conditions throughout the experiment. The structure of the sensor used in our experiment is enclosed in a closed arrangement of chamber, and it consisted of the vent hole that needs to directly touch with the skin to give true precise readings, within 1s of time duration. Ambient temperature and humidity readings were also taken with a commercial meter (HTC-1 Clock/Humidity/Temperature, Sinotimer, China) during each time of the experiment period. The experimental results of the indoor test indicated that, in most of the subjects, skin moisture was high during the morning and reduced in the evening; however, the results were quite different in the case of the outdoor environment.
The subjects were asked not to use any moisturizer cream after the start of the experiment. The indoor experiment was conducted at 10 AM, 2 PM, 4 PM, and 6 PM, and lasted 60 s in each case (Fig. 10). The outdoor experiment was conducted at 10 AM, 1 PM, 3 PM, and 5 PM, and lasted also 60 s in each case (Fig. 11). During the outdoor experiment, variations in ambient moisture and temperature greatly affected skin moisture. The subjects 1, 2, 3, and 4 of this experiment felt sweatier between 1 PM and 3 PM due to their exposure to strong sunshine; so their readings varied differently during the experimental analysis, this condition led to an increase in skin moisture.

In the Android app, the waterfall graphs showed the maximum and minimum skin moisture values registered at different timings of the day in the indoor and outdoor environments (Fig. 12). In the indoor environment, at 10 AM, the highest skin moisture value registered among the 8 subjects was of 73.3%, while the lowest value was of 55.21%. Instead, at 2 PM, 4 PM, and 6 PM, the highest (lowest) skin moisture values were of 65.97% (50.65%), 57.14% (47.45%), and 56.06% (37.42%), respectively. In the outdoor environment,
at 10 AM, the highest skin moisture value registered among the 6 subjects was of 55.68%, while the lowest was of 39.83%. Instead, at 2 PM, 4 PM, and 6 PM, the highest (lowest) skin moisture values were of 57.97% (33.95%), 59.62% (40.81%), and 56.12% (40.80%), respectively.

After that, machine learning techniques were also applied on the skin moisture data to define the actual values and make predictions through regression analysis. The 70% of data were taken by the machine to predict the skin moisture values based on the features of ambient humidity and ambient temperature. The analysis was based on the linear, bayesian (BRM), and decision forest (DFRM) regression models. It can be easily noted from the histograms of Fig. 13 that the coefficient of determination ($R^2$) was highest when using the DFRM, while it was lowest when using the BRM. DFRM proved to be highly accurate for the skin moisture analysis giving the value of $R^2$ to be 0.99. This means that the DFRM was highly accurate than others in predicting the skin moisture values, making the accuracy of this model to be 99%.

**B. UV IRRADIANCE MEASUREMENTS**

Skin moisture could also be reduced in a noticeable manner, whenever the skin is exposed directly to the sun; moreover, UV irradiance is a preemptive factor of skin damage [47], therefore in our skincare device, UV sensor has already been integrated which is capable of measuring the UVA, UVB and UVI radiations. The direct calculation of the UVI from the smartphone app would have not be appropriate, since it would have been based on the general and not specific geographical location [18], thus leading to erroneous results.

UV readings were taken by the UV sensor: it performed a continuous measurement of UVA and UVB radiations and transferred the data to the NFC smartphone. The measurements were started at 12 PM: the time corresponding to the most intense UVA and UVB irradiances. The experiment continued for $\sim 2$ h (depending on the smartphone battery), therefore, the UV dose was experimentally calculated using the following formula [48]:

$$D(t) = \left[ \frac{1}{2} \sum_{k=0}^{t} (I_k + I_{k+1})(t_{k+1} - t_k) \right]$$  \hspace{1cm} (4)

where $D(t)$ represents the amount of UV radiation measured at time $t$, $I_k$, and $I_{k+1}$ are the specific UV intensity readings at times $t_{k+1}$ and $t_k$. Figs. 14 (a), (b) represent the UVA and UVB exposure readings taken by the NFC smartphone, while the subjects were exposed to the outside environment. At the start of the experiment (12 PM), the sunshine was not very
bright and the sky was partially covered by clouds; therefore, the UVA and UVB readings fluctuated between 2000–5000 mW/m²/nm and 2000–8000 mW/m²/nm, respectively (Fig. 14(a) and Fig. 14(b)). UVA radiations are less powerful than the UVB radiations; still, they are highly penetrating and responsible for different types of cancer; meanwhile UVB radiations are extremely energetic and harmful for the skin, causing 65% of all skin tumors [49]. The UVI intensity is an index indicating the strength of sunburn produced and it is calculated from the UVA and UVB values while exposing to the sun. The UVI values range between 0 to 11+: 0 represents the low, while the range above 11 indicates the extreme range which has extremely harmful effects on the skin. Fig. 14(c) shows the UVI data obtained from the skincare device: the analysis started at 12 PM and continued for ∼ 2 h. Initially, the sky was partially covered by thick clouds, which disturbed the UVI measurements. Interestingly, the highest UVI values (> 6) were observed between 12 PM and 1 PM and were very harmful for the skin: our skincare device was able to provide accurate UVI values for a particular fixed location in order to support skincare.

VI. DEEP LEARNING ANN MODEL FOR OUTPUT PREDICTION AND SIGNAL CLASSIFICATION

A. MODEL DESIGN

In order to predict the exact output characteristics, the 6 channel inputs were passed to the ANN (its structure is shown in Fig. 15). Skin moisture, ambient humidity, skin temperature, ambient temperature, UVA and UVB intensities were provided as inputs while transepidermal water loss (TEWL), skin wetness factor (SWF), saturated vapor pressure skin (SVPS) and UVI were chosen as the outputs. The skin moisture sensor was able to provide skin moisture and temperature readings simultaneously by operating on two modes at the same time. Similarly, the UV sensor could provide UVA and UVB readings simultaneously. Meanwhile, ambient humidity and temperature values were measured using a commercial meter. Fig. 15 shows that the output vector $y_i$ of a single hidden neuron $i$ can be represented by:

$$y_i = f(w_{1i} \times \text{skin moisture} + w_{2i} \times \text{skin temperature} + w_{3i} \times \text{UVA} + w_{4i} \times \text{UVB} + w_{5i} \times \text{ambient humidity} + w_{6i} \times \text{ambient temperature} + b)$$

(5)

where $w_{ij}$ corresponds to the input weight for each input $x_j$ been given to neuron (where $j = 1, 2, 3, 4, 5, 6$), $b$ represents the bias hidden layer, and $f$ is the activation function of the neuron. The activation function chosen for each neuron is given by the following hyperbolic tangent sigmoid function:

$$f(X) = \tanh(X) = \frac{2}{1 + e^{-2X}} - 1$$

(6)

B. TRAINING THE ANN MODEL

In our study, we adopted a feedforward neural network model named Lavenberg-Marquardt (LM) backpropagation algo-

rithm to train the model. The LM algorithm was selected [50] because of its small size and ability in training networks, combining the advantages of gradient-descent and Gauss-Newton methods. Our data set was not very large and complex; therefore, the LM performed very well, resulting fast and accurate. The performance of the network was evaluated in terms of mean square error:

$$MSE = (predicted \ output – actual \ output)^2$$

(7)

The performance of the ANN depends on the number of hidden layers and that of neurons chosen for the experiment.

C. EFFECT OF THE HIDDEN LAYERS ON THE NETWORK PERFORMANCE

The training data of the 6 data inputs were passed to the ANN model with varying hidden layers. First, the performance of
the network was checked by considering a single hidden layer and varying the number of hidden neurons, \( N \) from 5, to 10, 15, and 20. When increasing \( N \) from 5 to 20, ANN takes more time to converge in order to obtain the lowest MSE. The best validation performance was observed for \( N = 20 \), while the lowest MSE was observed for \( N = 15 \) (Fig. 16). Hence, we can infer that the MSE did not improve by increasing the value of \( N \) to 20.

In order to enhance the performance of the ANN, its single hidden layer structure was shifted into a multilayer structure. The performance of the MSE was improved using a 2 layer ANN having \( N = 10 \) and \( N = 15 \) neurons. In this case, the MSE value was \( < 10^{-5} \); the best validation performance was achieved for a MSE value of \( 4.5251 \times 10^{-6} \) in epoch 15. The overall performance of the ANN in predicting the output data was not improved by further increasing the number of hidden layers. In summary, the performance of the network output prediction was successfully improved by employing a 2-hidden layer ANN model (Fig. 17): the predicted output was well correlated with the actual outputs.

**D. OUTPUT CLASSIFICATION ACCURACY**

The ANN was also used to classify the outputs into three categories: “less harmful”, “moderate harmful”, and “burn”. The experiment was conducted during the month of March in Busan, Korea; therefore, the average UVI values didn’t exceed 6 (which is considered to be in the high index range). In order to correctly predict the output, three classifiers were used to distinguish different levels of harmfulness: “less harmful” versus (“moderate harmful” and “burn”), “moderate harmful” versus (“less harmful” and “burn”), “burn” versus (“less harmful” and “moderate harmful”). The organization of the classifiers and the illustration of their performance was supported by the evaluation of the ANN performance and the determination of the receiver operating characteristics (ROC) graph [51]. The area under the curve (AUC) was used to evaluate the classification accuracy [51]:

\[
\text{accuracy} = \frac{TP + TN}{P + N} \tag{8}
\]

where the true positive rate of a particular classifier could be estimated from [51]:

\[
\text{True Pos Rate} = \frac{\text{Positives correctly classified}}{\text{Total Positives}} \tag{9}
\]

\[
\text{True Pos Rate} = \frac{TP}{P} \tag{10}
\]

Similarly, the negative positive rate of a particular classifier could be determined from [51]

\[
\text{True Neg Rate} = \frac{\text{Negatives correctly classified}}{\text{Total Negatives}} \tag{11}
\]

\[
\text{True Neg Rate} = \frac{TN}{N} \tag{12}
\]

The performance of the three classes evaluated by ANN classifier has been demonstrated in Fig. 18 by AUC and the values under classification accuracy has been elucidated in Table 3. Output classes were identified with an overall accuracy of 99.8%. Table 4 provides a complete concise description of the successful and wrong decisions taken for the three classes (i.e., “less harmful”, “moderate harmful”, and “burn”): thus it could be inferred from these results that the classification accuracy using ANN signifies an excellent performance for our training data.

**VII. CONCLUSION**

In this study, we designed a skincare device capable of harvesting energy from an NFC-enabled smartphone without the need for any battery, thereby providing support for the
skincare monitoring in cosmetic science. Skin moisture and UV sensors were used to obtain information that can be used beneficially for skincare. Moreover, deep learning techniques combined with an ANN model were used to predict the output of 6 channel inputs (MSE = 4.5251) combined with an ANN model were used to predict the classification of the outputs done using the ANN model was of 99.8% (the best classification performance achieved by the ANN in this study).

Our skincare device is 2.6 cm in diameter and can be easily transported by anyone with ease. Since the NFC technology is already enabled on the latest smartphones, these can be conveniently connected to our skincare device, enabling energy harvesting and data transfer. The proposed skincare device is enclosed in a 3D-printed object with a flexible design and can receive power from an NFC smartphone: the skincare device is self-powered and does not need any battery cell to operate. We also developed an Android skincare checkup app, which is capable of showing both the skin moisture and UVI data of the user.

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TABLE 3. Classification Accuracy of the AUC

| Class               | Accuracy | Mis-classification made by same Class | Mis-classification made by other Classes |
|---------------------|----------|--------------------------------------|-----------------------------------------|
| Less Harmful        | 0.998    | 0.002                                | 0.008                                   |
| Mod Harmful         | 0.998    | 0.002                                | 0.004                                   |
| Burn                | 0.998    | 0.002                                | 0.004                                   |

TABLE 4. Rate of Classification

| Class               | Successful Decisions | Unsuccessful Decisions |
|---------------------|----------------------|------------------------|
| Less Harmful        | 5845                 | 11                     |
| Mod Harmful         | 1018                 | 2                      |
| Burn                | 531                  | 0                      |

VOLUME 4, 2016
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