Assessing Transformer Oil Quality using Deep Convolutional Networks

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***Abstract*—Electrical power grids comprise a significantly large number of transformers that interconnect power generation, transmission and distribution. These transformers having different MVA ratings are critical assets that require proper maintenance to provide long and uninterrupted electrical service. The mineral oil, an essential component of any transformer, not only provides cooling but also acts as an insulating medium within the transformer. The quality and the key dissolved properties of insulating mineral oil for the transformer are critical with its proper and reliable operation. However, traditional chemical diagnostic methods are expensive and time-consuming. A transformer oil image analysis approach, based on the entropy value of oil, which is inexpensive, effective and quick. However, the inability of entropy to estimate the vital transformer oil properties such as equivalent age, Neutralization Number (NN), dissipation factor ($tan\delta$) and power factor (PF); and many intuitively derived constants usage limit its estimation accuracy. To address this issue, in this paper, we introduce an innovative transformer oil analysis using two deep convolutional learning techniques such as Convolutional Neural Network (ConvNet) and Residual Neural Network (ResNet). These two deep neural networks are chosen for this project as they have superior performance in computer vision. After estimating the equivalent aging year of transformer oil from its image by our proposed method, NN, $tan\delta$ and PF are computed using that estimated age. Our deep learning based techniques can accurately predict the transformer oil equivalent age, leading to calculate NN, $tan\delta$ and PF more accurately. The root means square error of estimated equivalent age produced by entropy, ConvNet and ResNet based methods are 0.718, 0.122 and 0.065, respectively. ConvNet and ResNet based methods have reduced the error of the oil age estimation by 83% and 91%, respectively compared to that of the entropy method. Our proposed oil image analysis can calculate the equivalent age that is very close to the actual age for all images used in the experiment.**

***Index Terms*—Transformer Oil Quality, Transformer Oil Age, Transformer Oil Image, Convolutional and Residual Neural Networks, Neutralization Number, Dissipation and Power Factors**

I. Introduction

Transformers are an important part of the electric power system. Thus, transformers' operating stability plays a significant effect on end-user daily operations and life comforts. During the lifetime of a power transformer, an interruption occurs for many reasons which affect the whole network and compromise other elements in the grid and produce a significant economic loss. For example, transformer breakdown incurred $286 million US dollars loss (property damage plus business interruption) in the year 1996 to 2001 [1]. There are two different insulation materials that exist in a transformer - (i) oil and (ii) the wrapping paper of the coil called insulation. To reduce the impact, over time, many transformer condition monitoring techniques have been introduced that are mainly based on transformer oil [2] [3] and insulation [4] condition monitoring.

The sound health of oil is crucial for transformers' proper operation. There are three main approaches for transformer oil condition monitoring - (i) Dissolved Gas Analysis (DGA) [4], (ii) Sulfur corrosion detection [3] [5] and (iii) Oil image analysis [6]. With age and the occurrence of various faults and deteriorations, oil degrades because of dissolved gases [4] [6] and other contamination's including sulfur deposited in it. The DGA and sulfur corrosion detection are found to be expensive, however, oil image analysis is relatively cheaper and requires less time, which motivates us to focus on oil image analysis. There are also several causes that can deteriorate transformer oil. The contact of atmospheric air with the oil triggers unwanted oxidation reaction in the oil. These reactions are further accelerated with high temperature and the presence of dissolved materials in the oil. As a result of these oxidation reactions, the color of the oil becomes darker, the resistivity (insulation level) of the oil decreases, concomitantly its acidity increases. As a consequence, the transformer dielectric dissipation factor ($tan\delta$) of the oil rises.

Changing the oil color plays a role in the oil deterioration process, which could be analyzed using the oil images to make a decision. To estimate the equivalent age and then neutralization number and dissipation factor, there exist an oil image analysis technique based on the entropy value of oil reported in [6]. This technique measures those interesting and important properties of the transformer oil, but it uses several intuitively derived constant values, and entropy value is not so effective for the age estimation. These limit the estimation accuracy. This technique does not work for more than 25 years of old oil. To improve the age estimation accuracy without using any threshold, in this paper, we propose an innovative oil image analysis using two deep convolutional learning techniques - (i) Convolutional Neural Network (ConvNet) and (ii) Residual Neural Network (ResNet). Experiment results show our both techniques significantly outperform the entropy-based approach.

The organization of the paper is as follows. Section 2 presents the related works, while the details as to how to prepare the training, validation and test sets from the selected images are given in Section 3. The description of the experimental set up is given in Section 4. Sections 5 and 6 present the results and their discussions and conclusions, respectively.

II. Related Work

Transformer condition monitoring techniques can be classified into two main categories: (i) Transformer insulation and (ii) Transformer oil condition monitoring.

A. Transformer Insulation Condition Monitoring

Transformer breakdowns occur because of insulation failure exhibited in the form of Partial Discharge (PD). For this reason, to monitor the condition of transformer insulation, there exist some approaches in the existing literature to detect the type of PDs based on their location information inside the transformer. One such contemporary approach for classifying PDs is presented in [4]. In this approach, Acoustic Emission (AE) sensors were used to collect the data. Using this data, a deep learning technique was applied to locate PDs. The main benefits of this approach are that it does not require feature extraction and the location detection accuracy is reasonably high. Even though the Random Forest (RF) classifier requires to use a conventional feature extraction technique, RF shows superior performance over deep learning, especially for the heated transformer oil. Note, PD also deteriorates the oil condition.

Aging of transformer oil affects its productive life and utility. Since the transformer oil age has a great influence over its condition, over time, researchers in the relevant community introduced many techniques to monitor the condition of transformer oil. Some of these recent techniques are presented in the following section.

B. Transformer Oil Condition Monitoring

Transformer oil condition monitoring can be performed in three ways - (i) Dissolved gas analysis (DGA), (ii) Sulfur corrosion detection and (iii) Oil image analysis. The major gases generated from the faults are Hydrogen (H_2), Methane (CH_4), Acetylene (C_2H_2), Ethane (C_2H_4), Carbon Monoxide (CO), Carbon dioxide (CO_2) which are also called as key gases and dissolved in oil. The first way analyzes these dissolved gases. Liang et al. [2] introduced a DGA technique, which has already been proven an effective method to diagnose the internal fault of transformers for decades. This technique uses a deep learning technique called Deep Belief Networks (DBN). With composed of restricted Boltzmann machines, DBN can build the mapping relationship between the characteristic gas and the fault types automatically to achieve an accurate diagnosis.

Mineral oils contain a number of corrosive sulfur compounds like elemental sulfur, mercaptans, and sulfides. Dibenzyl disulfide (DBDS) is used to protect the transformer from oxygen ingestion during operation. DBDS appears to be non-reactive, however, because of degradation, it turns into benzyl mercaptan, a highly reactive compound to copper. By reaction with copper, Benzyl mercaptan creates copper sulfide (Cu_2S). There are many instances of transformer breakdown for sulfur corrosion [7], motivating the researchers to develop techniques (e.g. Gas Chromatograph, X-ray fluorescence spectrometry, Sensor-based techniques) to detect it [3] [5]. Gas Chromatograph and sensor-based techniques measure the amount of DBDS, while X-ray fluorescence spectrometry estimates the amount of insulation oil corrosion level. However, Gas Chromatograph and X-ray fluorescence spectrometry are expensive and sensor-based techniques require the least amount of time (e.g., one day) to detect DBDS.

To reduce the expense and provide the instant analysis of transformer oil, Sidram and Hegde [6] introduced an approach to estimate the equivalent age of transformer oil using an image analysis technique. By calculating the entropy value of the oil image, this approach estimates the sample oil equivalent aging year, neutralization number, $tan\delta$ and power factor. This is a fundamental idea to use entropy in calculating equivalent oil age. However, the approach is based on many intuitively selected thresholds, and entropy cannot represent the oil age well, which limit its efficacy.

To improve the age estimation accuracy without using any threshold, we need to introduce a new technique which is the main focus of this paper.

III. Dataset

Typically a large amount of data is required to train a deep learning network to achieve an acceptable learning success rate. Since in any electrical power system, there was not any particular requirement to collect and store the transformer oil images with metadata (e.g., age). For this reason, sufficient transformer oil images are not available to use in our experiment. Sidram et al. used a set of authentic transformer oil images (10 images) in their project presented in [6]. Figure 3 shows those 10 images tagged with their actual ages. We used that set of images to generate in a total of 36480 samples[1] having 3648 samples per image for our deep learning networks to feed. The size of each sample was 32×32. These 10 images were divided horizontally in the middle, the upper part was sampled for the training and validation data, while the lower part was for the testing data. For each class, our dataset consists of 2400 samples in the training, 480 samples for the validation and 1000 samples for the test sets. Note, for the classification using a deep learning network, we used a class for each of the 10 images.

IV. Experiments

The goal of the experimental study is to classify the transformer oil image to its corresponding equivalent age using several classification algorithms to get the best performance. By knowing the age of the oil, the dissipation factor ($tan\delta$)

[1]https://github.com/whilemind/transformer-data

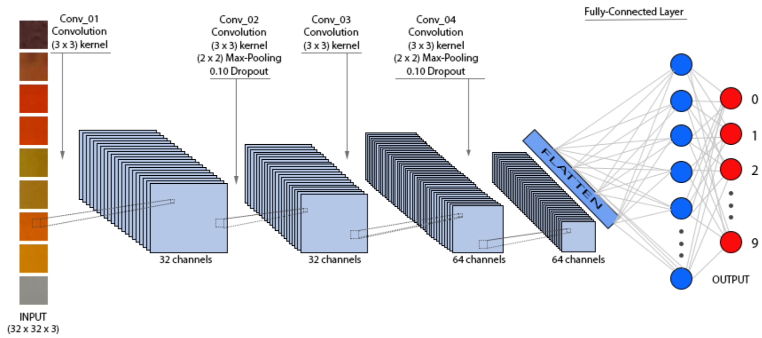

Fig. 1. Convolutional neural network.

can be calculated from Eq. (7) and power factor from Eq. (10) which gives a clear view of the efficiency of the transformer oil.

Classification algorithms are very powerful techniques that intelligently discriminate an object from others by exploiting their distinctive features. Many different classification algorithms are available with significant differences in performance in different application domains. The Convolutional Neural Network (ConvNet) and Residual Neural Network (ResNet) are well-known classifiers as these two networks can effectively differentiate an object from others. Some primitive classification algorithm requires to hand-engineered the filters where ConvNet and ResNet can learn those filters or object characteristics automatically from the data with the proper training.

Three experiments were performed in three different methods to find out the best result. Those techniques are (i) Entropy (ii) ConvNet and (iii) ResNet. Python programming language was used to perform all the development and data processing in these experiments. It's concise and intuitive syntax allows the rapid development of a variety of different applications and tools. It also has a wide variety of toolboxes that can support most scientific and technical computing tasks. Classification algorithms (ConvNet and ResNet) were implemented using Keras on top of Tensorflow for the CNN, a commonly used and flexible Python machine learning toolkit.

A. *Entropy Technique*

To present the comparative performance of our proposed approach, we implemented the entropy based approach according to the algorithm, threshold values and description provided in [6] and found quite different estimated ages (refer to Table I) than their values reported in this paper. For clarification, the algorithm and other aspects used in implementation are described below:

In implementation, the algorithm from the Sidram et al. [6] was exactly followed except the resize of images because the resizing parameters are not clearly specified in the paper. Eq. (1) was used to calculate the entropy of an oil image:

$$E = -\sum_{k} p_k log_2(p_k) \tag{1}$$

where, p_k represents the normalized k^{th} bin count of a histogram.

The equivalent aging year was calculated by Eq. (2) from the entropy value derived from Eq. (1).

$$Y = \frac{(E_1 - E_0)}{k_1} \tag{2}$$

where, E_0 and E_1 are the entropy of the fresh and sample oils, respectively. k_1 was assumed as 0.046.

Algorithm 1 was used in our experiment for entropy based technique. The color image was loaded (Step 2 of Algorithm 1) and converted to a grey scale image (Step 3), the median filter was applied with a 5×5 filter (Step 4). After that histogram count was performed (Step 5) and then used it as argument to calculate the entropy using the $entropy$ function (Step 6).

Algorithm 1 Entropy algorithm

1: **procedure** ENTROPY($imgPath$)
2: $rgbImg \leftarrow imread(imgPath)$
3: $greyImg \leftarrow rgb2grey(rgbImg)$
4: $filtImg \leftarrow median(greyImg, filter)$ ▷ filter 5X5
5: $counts \leftarrow histogram\_count(filtImg)$
6: $ent \leftarrow entropy(counts, base)$ ▷ base 2
7: **return** ent
8: **end procedure**

As mentioned before, the estimated ages by our implementation of [6] (Algorithm 1) are given in Table I. Table I shows the estimated ages are quite different from the actual transformer oil ages. For example, the estimated equivalent age of three years old sample oil is 20.43 years, whereas, it is reported as 2.60 years in their paper. For this huge discrepancy between the implemented and reported results produced by [6], we will present the performance of our proposed approach comparing with their reported results in the rest of the paper.

B. *ConvNet*

The ConvNet used in the experiment consisted of five convolutional layers where 32 filters of kernel size 3×3 were used in the first and second convolution layers with Rectified Non-Linear unit (ReLU). After these two hidden layers, max

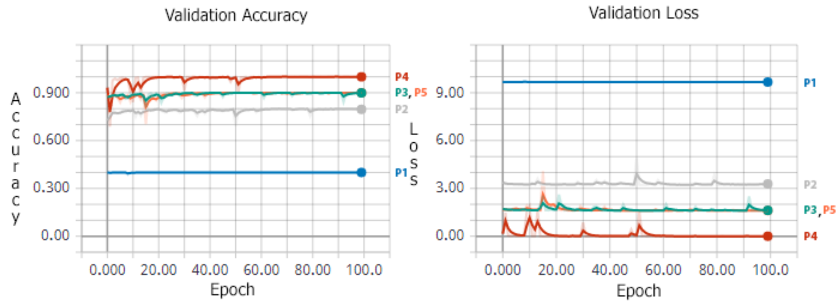

Fig. 2. ConvNet Training Validation Graph. Legends: 1st training phase,

TABLE I
ESTIMATED AGES DERIVED USING ENTROPY BASED TECHNIQUE [6]

Sample Year	Calculated Entropy Value	Estimated Aging Year
1.00	2.43	1.00
3.00	3.37	20.43
9.00	4.16	37.60
12.00	4.30	40.65
14.00	4.08	35.86
16.00	4.09	36.08
17.00	4.24	39.34
18.00	4.37	42.17
21.00	3.30	18.91
25.00	3.75	28.69

pooling was used having a size of 2×2 followed by a Dropout Layer [8] of value 0.10. The above two convolution layers were repeated once again with 64 filters having 3×3 kernel followed by a 2×2 max pooling and the dropout layer value as 0.10. Then the flatten layer was added with a dropout layer of value 0.20, which was fully connected with a softmax layer. The diagram of the network is given in Figure 1. Here, the best training models produced by this network are regarded as those models that produced validation accuracy ≥ 0.98.

How ConvNet's validation accuracy and validation loss vary with the number of epochs are shown in Figure 2 which show they change considerably up to 15 epochs. In this figure, as representative examples, five training phases (P1 to P5) are shown in five different colors where each of the phases consisted of 100 epochs. For this reason, to automatically select the best training models, those models whose epoch was greater than 5 and validation accuracy was between 0.98 to 1.0 were chosen to calculate the equivalent ages. The performance of such training models in terms of accuracy and estimated equivalent ages compared with the relevant actual oil ages is shown in Table II. For example, for epoch=13 and accuracy=0.988, the estimated equivalent age of 16 years old oil is 16.14.

C. Residual Neural Network (ResNet)

Deep Residual Network [9] is the most groundbreaking work in the deep learning community in the last few years. It makes it possible to train up to hundreds or even thousands of layers and still achieves promising performance. The most

TABLE II
EQUIVALENT OIL AGES ESTIMATED BY CONVNET MODELS

		Year (1^{st} row shows the actual oil ages; others are their estimated values)									
Epoch	Accuracy	1	3	9	12	14	16	17	18	21	25
10	0.983	1.0	3.0	9.0	12.0	14.0	15.86	16.84	18.0	21.0	25.0
12	0.994	1.0	3.0	9.0	12.0	14.0	16.64	16.95	18.0	20.95	22.04
13	0.988	1.0	3.04	9.0	12.0	14.0	16.14	16.86	18.0	20.83	24.91
14	0.988	1.0	3.0	9.0	12.0	14.0	16.13	16.89	18.0	20.83	25.0
18	0.99	1.0	3.53	9.0	12.0	14.0	16.16	16.9	18.0	21.0	25.0
20	0.992	1.0	3.05	9.0	12.0	14.0	16.14	16.87	18.0	21.0	25.0
22	0.996	1.0	3.0	9.0	12.0	13.82	16.45	16.95	18.0	21.0	25.0
23	0.994	1.0	3.0	9.0	12.0	13.57	16.15	16.89	18.0	21.0	24.65
23	0.996	1.0	3.37	9.0	12.0	13.87	16.19	16.93	18.0	21.0	25.0
30	1.0	1.0	3.0	9.0	12.0	13.69	16.61	16.96	18.0	21.0	24.21
35	0.996	1.0	3.0	8.66	12.0	13.45	16.22	16.91	18.0	21.0	25.0
39	0.999	1.0	3.0	9.0	12.0	13.85	16.19	16.95	18.0	21.0	23.9
43	0.998	1.0	3.0	9.0	12.0	14.0	16.05	16.88	18.0	21.0	25.0
52	0.998	1.0	3.0	9.0	12.0	14.0	16.13	16.89	18.0	21.0	25.0
53	0.998	1.0	3.0	9.0	12.84	13.73	16.2	16.92	18.0	21.0	25.0
54	0.999	1.0	3.0	9.0	12.0	14.0	16.42	16.94	18.0	21.0	25.0
57	1.0	1.0	3.0	9.0	12.28	14.0	16.64	16.96	18.0	21.0	25.0
61	1.0	1.0	3.0	9.0	12.0	14.0	16.27	16.94	18.0	21.0	25.0
62	1.0	1.0	3.0	9.0	12.0	14.0	16.16	16.92	18.0	21.0	25.0
69	1.0	1.0	3.0	9.0	12.0	13.76	16.14	16.89	18.0	21.0	25.0
72	1.0	1.0	3.0	9.0	12.0	13.8	16.14	16.89	18.0	21.0	24.99
Average of est. ages		1.00	3.05	8.98	12.05	13.88	16.24	16.91	18.00	20.98	24.75

significant innovation on the network is to skip connections or short-cuts to jump over some layers. Typically, it uses double of triple-layer skips that contain nonlinearities (ReLu) and batch normalization in between. Skipping over layers motivation contributes to avoiding the well-known vanishing gradients problem.

To show how good is ResNet in classification, a confusion matrix showing the classification of oil ages is given in Table III using the model in which validation accuracy was the best of all the trained models in ResNet. The high classification accuracy indicates how closely it was able to predict the oil ages.

TABLE III
RESNET CONFUSION MATRIX SHOWING THE CLASSIFICATION OF OIL AGES

Oil Age in Year	1	3	9	12	14	16	17	18	21	25
1	1000	0	0	0	0	0	0	0	0	0
3	0	1000	0	0	0	0	0	0	0	0
9	0	0	1000	0	0	0	0	0	0	0
12	0	0	0	1000	0	0	0	0	0	0
14	0	0	0	0	1000	0	0	0	0	0
16	0	0	0	0	0	1000	0	0	0	0
17	0	0	0	0	0	83	917	0	0	0
18	0	0	0	0	0	0	0	1000	0	0
21	0	0	0	0	0	0	0	0	1000	0
25	0	0	0	0	0	0	0	0	0	1000

Similarly to ConvNet, only the ResNet learning models whose *epoch* > 5 and validation accuracy $\in$ [0.98, 1.0] were

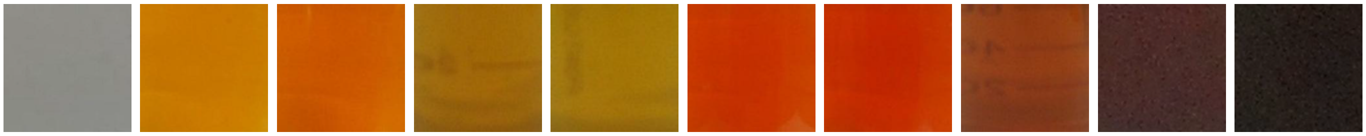

Fig. 3. Transformer oil sample images having age from the top left corner to the right are 1, 3, 9, 12, 14, 16, 17, 18, 21 and 25 years old, respectively.

selected to calculate the equivalent ages, as shown in Table IV.

TABLE IV
EQUIVALENT OIL AGES ESTIMATED BY RESNET MODELS

		Year (1^{st} row shows the actual oil ages; others are their estimated values)									
Epoch	Accuracy	1	3	9	12	14	16	17	18	21	25
5	0.987	1.0	3.0	9.0	12.0	14.0	16.07	16.84	18.0	21.0	25.0
6	0.992	1.0	3.0	9.0	12.0	13.73	16.19	16.87	18.0	21.0	25.0
8	0.999	1.0	3.0	9.0	12.0	14.0	16.38	16.91	18.0	21.0	25.0
12	0.998	1.0	3.0	9.0	12.0	13.23	16.16	16.88	18.0	21.0	25.0
18	0.994	1.0	3.0	9.0	12.0	14.0	16.03	16.86	18.0	21.0	25.0
19	0.996	1.0	3.0	9.0	12.0	14.0	16.0	16.82	18.0	21.0	25.0
23	0.994	1.0	3.0	9.0	12.0	14.0	16.0	16.83	18.0	21.0	25.0
24	0.999	1.0	3.0	9.0	12.0	14.0	16.23	16.9	18.0	21.0	25.0
25	0.999	1.0	3.0	9.0	12.0	13.87	16.01	16.84	18.0	21.0	25.0
37	1.0	1.0	3.0	9.0	12.0	14.0	16.23	16.91	18.0	21.0	25.0
54	0.998	1.0	3.0	9.0	12.0	14.0	16.0	16.79	18.0	21.0	25.0
58	0.998	1.0	3.0	9.0	12.0	13.66	16.02	16.82	18.0	21.0	25.0
63	1.0	1.0	3.0	9.0	12.0	14.0	16.12	16.9	18.0	21.0	25.0
73	0.999	1.0	3.0	9.0	12.0	13.97	16.05	16.89	18.0	21.0	25.0
Average of est. ages		1.00	3.00	9.00	12.00	13.89	16.11	16.86	18.00	21.00	25.00

V. COMPARATIVE RESULTS

In this section, for comparison, all the results produced after conducting the experiments are presented and discussed. However, before giving them, the formulae that were used to create the results are articulated.

Equivalent Age Estimated from Deep Learning Classification ($C^{(i)}$): Eq. (3) was used to calculate the equivalent age of i^{th} year old oil using the classification results produced by a deep learning model.

$$C^{(i)} = \left(\sum_{i=1}^{n} Y^{(i)} \hat{Y}^{(i)} \right) / S_{count} \tag{3}$$

where, $Y^{(i)}$ is the value of i^{th} year; $\hat{Y}^{(i)}$ is the accurate classification count produced by a deep learning model for i^{th} year and S_{count} is total sample count used in the test set.

Root Mean Squared Error (RMSE): RMSE is a measure of inaccuracy to compare the forecasting errors of different models for a particular variable and not between variables as it is scale-dependent [10]. RMSE presents the variance of the error distribution. For a target sequence d and forecast sequence f with n time steps, it is calculated by Eq. (4).

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(d_i - f_i \right)^2} \tag{4}$$

where, d_i represents the sample year value and f_i is the value from different methods like Entropy, ConvNet, and ResNet. In this paper, RSME (Eq. (4)) was used to calculate the error of the three different methods compared with a set of standard values (a target sequence).

Acid Neutralization Number (NN): The acid neutralization number, or acid number, is the amount of potassium hydroxide (KOH) in mg required to neutralize the acid in one gram of oil. It indicates the acid level in the oil. With service-aged oils, it also represents the presence of contaminants, like sludge. NN is defined in [6] as,

$$NN = A_c \times Y \tag{5}$$

where, A_c and Y are the acid constant (will be defined later) and oil age, respectively. For mineral oil, the acid number found less than $0.05mg\ KOH/gram$ in the new oil and the sludge starts forming when the acid number goes to greater than $0.4mg\ KOH/gram$. Typically, the value of $0.10mg$ $KOH/gram$ or less than, considers good and higher values indicate a problem.

Acid Constant (A_c): In [6], to acquire NN, the following two acid constant values are taken. The reason behind this is that the acidity is not constantly rising.

$$A_c = \left\{ \begin{matrix} 0.0130 \text{ when } 0 \le Y \le 14 \\ 0.0159 \text{ when } 15 \le Y \le 25 \end{matrix} \right\} \tag{6}$$

where, Y is the estimated equivalent oil age derived using Eq. (1).

Dissipation Factor ($tan\delta$): The dissipation factor is calculated using Eq. (7):

$$tan\delta = Y \times K \tag{7}$$

where, $Y \neq 0$ and $Y = 1$ for the fresh oil and as alluded in [6], K is a constant whose value differs with oil age range according to Eq. (8).

$$K = \left\{ \begin{matrix} 0.00210 \text{ when } 0 \le Y \le 14 \\ 0.00719 \text{ when } 15 \le Y \le 25 \end{matrix} \right\} \tag{8}$$

The value of K was calculated from the standard test value of $tan\delta$ which is,

$$K = \frac{(\text{Final } tan\delta \text{ value from standard test})}{Y} \tag{9}$$

Power Factor (PF): Power factor indicates the dielectric loss of insulating oil, and thus it's dielectric heating. The power-factor test is widely used as an acceptance and preventive maintenance test for insulating oil. A high power factor in service-aged oil indicates deterioration, contamination or both with moisture, carbon or deterioration products. For mineral oil, the power factor of new oil should not exceed 0.05% at 25^oC. The power factor has a relation with the dissipation factor and is calculated using Eq. (10):

$$PF = \sqrt{\frac{tan\delta^2}{1 + tan\delta^2}} \tag{10}$$

TABLE V
CALCULATED AND STANDARD VALUES OF NN, $tan\delta$ AND $sin\delta$

Actual Oil Age in Year	1	3	9	12	14	16	17	18	21	25	RMSE
Neutralization Number (NN)											
Standard	0.013	0.050	0.117	0.156	0.223	0.254	0.270	0.286	0.334	0.398	
Entropy	0.013	0.043	0.138	0.167	0.225	0.256	0.287	0.290	0.336	0.387	0.0102
ConvNet	0.013	0.051	0.117	0.157	0.221	0.258	0.269	0.286	0.334	0.393	0.0015
ResNet	0.013	0.050	0.117	0.156	0.221	0.256	0.268	0.286	0.334	0.398	0.0010
Dissipation factor ($tan\delta$)											
Standard	0.002	0.006	0.019	0.025	0.029	0.115	0.122	0.129	0.150	0.179	
Entropy	0.002	0.005	0.022	0.027	0.030	0.115	0.129	0.131	0.151	0.174	0.0031
ConvNet	0.002	0.006	0.019	0.025	0.029	0.116	0.121	0.129	0.150	0.177	0.0008
ResNet	0.002	0.006	0.019	0.025	0.029	0.115	0.121	0.129	0.150	0.179	0.0003
Power factor ($sin\delta$)											
Standard	0.002	0.006	0.019	0.025	0.029	0.114	0.121	0.128	0.149	0.176	
Entropy	0.002	0.005	0.022	0.027	0.030	0.114	0.128	0.130	0.150	0.172	0.0029
ConvNet	0.002	0.006	0.019	0.025	0.029	0.115	0.120	0.128	0.149	0.174	0.0008
ResNet	0.002	0.006	0.019	0.025	0.029	0.115	0.120	0.128	0.149	0.176	0.0004

A. Comparative Analysis

For equivalent age estimation (refer to Table VI), the RMSE of ConvNet and ResNet are 0.122 and 0.065, respectively, while it is 0.718 for the entropy based technique [6]. Table VI shows for measuring the equivalent oil ages, both ConvNet and ResNet outperform entropy based technique and ResNet produces the best performance as it has the lowest RMSE value (0.065). Similarly, with respect to standard values, as shown in Table V, the RMSE errors of ConvNet and ResNet for NN and dissipation factor and power factor are 0.0015 & 0.0010, 0.0008 & 0.0003 and 0.0008 & 0.0004, respectively, while they are 0.0102, 0.0031 and 0.0029 for entropy based technique. Lower ConvNet and ResNet's RSME errors indicate their estimated values are very close to the respective standard values.

TABLE VI
ESTIMATED EQUIVALENT OIL AGES

Sample Year	Entropy's Year	ConvNet's Year	ResNet's Year
1.00	1.00	1.00	1.00
3.00	**2.60**	**3.05**	3.00
9.00	**10.65**	**8.98**	9.00
12.00	**12.82**	**12.05**	12.00
14.00	**14.15**	**13.88**	**13.89**
16.00	**16.08**	**16.24**	**16.11**
17.00	**18.02**	**16.91**	**16.86**
18.00	**18.26**	18.00	18.00
21.00	**21.15**	**20.98**	21.00
25.00	**24.34**	**24.75**	25.00
RMSE	0.718	0.122	0.065

VI. CONCLUSIONS

In this paper, we introduce an image analysis technique using two deep convolutional networks to estimate the equivalent ages of transformer oils. Overall, the estimated equivalent ages appear to be highly accurate and thus, the proposed technique strongly appeals to its application to identify faults in power transformers. It could also be used in developing an online power transformer monitoring system. The accuracy of the proposed technique to calculate equivalent ages and then neutralization numbers and dissipation and power factors shows the importance of deep learning application in the integrated power system to improve its reliability and reduce its failure.

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