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**Predicting Cesarean Related Surgical Wound Infection in Rwandan Patients**

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**1. Overview**

In rural East Africa, over half of all surgeries are performed through the cesarean sections[1]. Women who undergo these surgeries seldom receive clinical oversight after discharge, and about 10-15% of them develop Surgical Site infections (SSIs) [2]. SSI is also the leading cause of female mortality in Rwanda[3]. Delay or failure to seek treatment for an SSI can lead to considerable morbidity or death. This work aimed to develop and validate a model to assist community health workers (CHWs), specifically for a third world country like Rwanda, helping surgeons identifying SSIs and referring women to care. Our work was a follow-up to a randomized controlled trial conducted at Kirehe District Hospital in Rwanda by Bethany L Hedt-Gauthier et al. We use the results of this experiment as a baseline for evaluating our models.

Patients at the Kirehe District Hospital who were at least 18 years old and underwent caesarean sections between November 2017 and November 2018 were eligible for the study. The selected patients were randomly assigned to one of three arms. Patients in arm 1 were visited at their homes by a CHW 10 (±3 days) after their operation and the CHW administered an SSI screening protocol using an electronic tablet. Patients in arm 2 were screened over the phone by CHWs. Patients in both arms 1 and 2, who responded ‘yes’ to any of the screening questions were referred to a health facility. Arm 3 patients did not receive screening or follow-up healthcare. The impact of the CHW intervention on the rate of return to care for patients with SSIs was used as the main outcome metric. The models we created were based on patient data from a set of routine questions that were used to derive the screening questions used by CHWs in the randomized study. We also used cell phone images of patient wounds as data for our models.

In our experiment, three models were created that classified patients as Infected or Not-infected after the surgery. The first model used only their questionnaire responses which consisted of a set of 10 questions that were asked to every patient that had gone through with the surgery. The second model used patient wound images that were taken using a standard mobile camera. And, the third model that combined the results of the first two models to provide an integrated and comprehensive output. The results of all three models were then compared.

The patient questionnaire consisted of the following standard questions:

* Has the patient experienced fevers since the surgery?
* Has the patient experienced pain around the incision?
* Is there redness around the incision?
* Is there swelling around the incision?
* Is there firmness around the incision?
* Is there draining?
* Is the draining thick or thin?
* What color is the draining?
* Does the draining have a smell?
* Is there a gape around the incision?

**1.1 Questionnaire Model**

For our questionnaire model, the program started by reading in a spreadsheet of patient responses into a data matrix as displayed in *Fig.1*. The data had 582 rows and 12 columns, each corresponding to patients in the study. The first column corresponding to the patients’ ID in the study, the next 10 columns describe the patients’ responses to each of the questions and the last column being a Yes/No indicator of whether or not the patient had an SSI. It was observed that 10 patients had some combination of the ‘redness’, ‘swelling’, ‘firmness’, ‘draining’, and ‘gape’ features missing, so those patients were dropped from our dataset. Of the remaining 572 patients in our data, 61 were found to have SSI. Also, it was observed that the answers to features like ‘draining\_thickness’, ‘draining\_color’ and ‘draining\_smell’ were dependent on whether there was any kind of draining taking place. If a patient’s wound had no draining, then these questions had no answers, so their values were missing in the data. These questions were all categorical values in the data that took on two values. The responses to ‘draining\_thickness’ were either ‘Thick’ or ‘Thin’, whereas ‘draining\_color’ took on a set of values in the form of ‘Brown, yellow, green, white’ or ‘Red, pink, clear’ and ‘draining\_smell’ was either Yes or No variable. We split these columns into two features indicating whether the patients’ answers took on either of the two values. In other words we replaced the column containing ‘draining\_thickness’ with two columns: ‘thick\_draining’ and ‘thin\_draining’. Both columns took binary values 0 or 1. A similar structure was created for the other two draining dependent variables. Our dataset now consisted of 13 features with the added columns. Among the 10 standard questions, the best set of questions included fever, pain and drainage.

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Id | Fever | Pain | Redness | Swelling | Firmness | Draining | Thick Draining | Thin Draining | Brown, Yellow, Green, White Draining | Red, Pink, Clear Draining | Draining with Smell | Draining without Smell | Gape | SSI |
| 1 | Yes/No | Yes/No | Yes/No | Yes/No | Yes/No | Yes/No | Yes/No | Yes/No | Yes/No | Yes/No | Yes/No | Yes/No | Yes/No | Yes/No |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |
| 572 | Yes/No | Yes/No | Yes/No | Yes/No | Yes/No | Yes/No | Yes/No | Yes/No | Yes/No | Yes/No | Yes/No | Yes/No | Yes/No | Yes/No |

*Fig.1. Table displaying the new dataset created by removing missing variables and splitting all drainage features.*

Once the new dataset was created, two logistic regression models - one with L1 penalty and the other with L2 penalty we formed. Models with L1 penalties tend to discard features that are not relevant for classification, while L2 penalized models try to optimize prediction using all features, so we used both penalties to determine if any of the questions were irrelevant and what effects they had on the model results. We trained these models as well as a Support Vector Machine (SVM) classifier on our transformed data.

**1.2 Image Model**

For our wound image model, cell phone images of 568 patients are read. Of these, 62 were images from patients with SSIs, while the remaining 506 were images of uninfected wounds. The images were escalated to a common size of 160x340 pixels (width x height). Each image was also converted from an RGB (red-green-blue) color space to a LAB color space. The LAB system expresses colors with respect to three components: L (luminance), A (green-red) and B (blue-yellow). It was designed to be consistent with the way that humans perceive color; in other words the numerical difference between two colors in LAB space directly corresponds to the perceived difference between these colors by the human eye. Several features from each image were then extracted. The first set of image features consisted of the local Gabor binary pattern histograms for each of the 9 blocks obtained by performing a 3x3 split of the image[4]. These values are obtained by first applying a Gabor filter over the image. A Gabor filter is a linear filter used to analyze image texture by measuring the occurrence of frequency content in a specified direction in a given area of an image. After filtering the image, the local binary pattern for each pixel in computed, which is obtained by comparing indicators of whether each pixel is greater than each of its eight neighbors and creating a binary integer out of these indicators. A histogram is then evaluated for each block from the binary patterns of all of the pixels in the block. The histogram values are used as features that convey information on the presence of different textures in each image block. A total of 7200 feature values were obtained per image from the local Gabor binary pattern histograms. The second set of image features were derived from a histogram over each of the three components of each image, resulting in 512 features per image. The final set of features were derived by dividing each image into 8 blocks (4 rows x 2 columns) and computing the mean, variance, and skewness of the pixel values in each block for each component of the image. This resulted in 72 features (3 components x 8 blocks/component x 3 features/block)[5]. In total, 7784 features were derived for each image. Each of these features were standardized in our dataset to account for differences in scale. Because there were such a large number of features (7784) compared to our sample size (568), it’d be useful to perform variable selection on our data. In turn, a logistic regression model with an L1 penalty was trained on the derived features.

**1.3 Combined Model**

For the combined model, datasets of the 572 patient questionnaire responses and 568 wound images are merged. However, the patients in the two datasets didn’t perfectly correspond and the patients that possessed both questionnaire responses and wound images were 552. Thus, the data for these patients was merged and an augmented dataset was obtained. The questionnaire features in this dataset were converted to integers (1 for yes response, 0 for no) and their values were normalized to be consistent with the normalized values of the image dataset. This resulted in a dataset with 7797 features corresponding to the 13 features from the questionnaire dataset and the 7784 from the images. A similar logistic regression model with L1 penalty was used upon this data.

For all of our models, we evaluated them on 100 randomly generated splits of the complete dataset, with 75% of the patients’ data being used to train the model and the remaining 25% (roughly 140 patients) being held out for testing. We kept track of several evaluation metrics for each split of the data and report the median value and range for each metric in the results section.

**2. Results**

**2.1 Questionnaire Model**

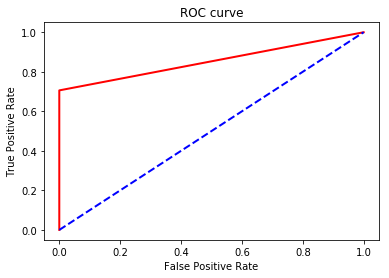
**2.1.1 L1 Logistic Regression**

For our L1 penalized model, the following results achieved are displayed in the confusion matrix below. The model had a median accuracy of 95.80% with values ranging from 92.31% to 100%. Its sensitivity and specificity values were 0.7134 (0.4545 - 1.0) and 0.9846 (0.9627 - 1.0) respectively.

|  |  |  |  |
| --- | --- | --- | --- |
|  |  | Predicted Class | |
|  |  | Not Infected | Infected |
| Actual Class | Not Infected | 126 (117 - 133) | 2 (0 -5) |
| Infected | 5 (0 - 9) | 11 (5 - 17) |

*Confusion Matrix for L1 Logistic Regression Model*

The area under the Receiver Operating Characteristic (ROC) curve was 0.8529 (0.7235 - 1.0) as shown in *fig.2*.



*Fig.2. ROC curve for L-1 Penalized Model*

The coefficient value of a feature displays its importance on the machine learning model used. Higher the coefficient value, greater is its influence on the model. Given below is the Coefficient Value table (*table.1*) for the above model. The L1 penalized model determined that the swelling, thin draining, draining color (red, pink, clear), and draining without smell variables weren’t relevant for prediction. It makes sense that the latter three features were determined irrelevant, as their values can be inferred using the other two related features in the dataset.

|  |  |
| --- | --- |
| **Feature** | **Coefficient Value** |
| Draining with smell | 3.61 (2.78 — 4.46) |
| Draining color (Brown, Yellow, Green, White) | 2.23 (1.05 — 3.32) |
| Fever | 0.97 (0 — 1.73) |
| Pain | 0.95 (0 — 1.84) |
| Thick draining | 0.95 (0 — 2.29) |
| Draining | 0.50 (0 — 1.43) |
| Firmness | 0.49 (0 — 1.34) |
| Gape | 0.12 ( 0 — 1.34) |
| Redness | 0.09 (0 — 1.86) |

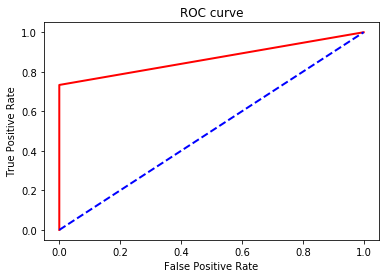
*Table.1. Coefficient Value table for the different features from the questionnaire.*

**2.1.2 L2 Logistic Regression**

The L2 penalized model had a median accuracy of 96.50% with values ranging from 91.61% to 99.30%. Its median sensitivity was 0.75 with values ranging from 0.4118 to 0.9333, and its specificity was 0.9921 on average but ranged from 0.9615 to 1.0. The area under the ROC curve was 0.8666 (0.7058 – 0.9666), and the corresponding curve is displayed in *fig.3*. The (averaged) confusion matrix was as follows:

|  |  |  |  |
| --- | --- | --- | --- |
|  |  | Predicted Class | |
|  |  | Not Infected | Infected |
| Actual Class | Not Infected | 126 (119 - 133) | 1 (0 -5) |
| Infected | 4 (1 - 11) | 11 (5 - 18) |

*Confusion Matrix for L2 Logistic Regression Model*



*Fig.3. ROC curve for L-2 Penalized Mode*

Similarly, the coefficient values for the features in the second regression model in order of magnitude are displayed in *table.2.* Comparing the results of the two coefficient values for the different features of the questionnaire, it is observed that the values for the features in a L2 logistic model reduces in comparison with the L1 logistic model since the L1 model removes the features that are of minor value.

|  |  |
| --- | --- |
| **Feature** | **Coefficient Value** |
| Draining with smell | 2.01 (1.76 — 2.31) |
| Draining color (Brown, Yellow, Green, White) | 1.62 (1.32 — 2.03) |
| Draining | 1.29 (1.07 — 1.53) |
| Thick Draining | 1.15 (0.69 — 1.52) |
| Draining without smell | -0.83 (-1.22 — -0.61) |
| Fever | 0.81 (0.01 — 1.29) |
| Pain | 0.76 (0.10 — 1.16) |
| Redness | 0.56( -0.51 — 1.24) |
| Swelling | 0.51 (-0.30 — 1.21) |
| Gape | 0.50 (-0.07 — 1.11) |
| Firmness | 0.44 (-0.47 — 0.98) |
| Draining color (Red, Pink, Clear) | -0.33 (-0.96 — 0.02) |
| Thin draining | 0.11 (-0.22 — 0.56) |

*Table.2. Coefficient Value table for the different features from the questionnaire.*

**2.1.3 Support Vector Machine**

Support Vector Machine (SVM) is an algorithm used for classification problems similar to Logistic Regression (LR). LR and SVM with linear Kernel generally perform comparably in practice. The objective of the support vector machine algorithm is to find the hyperplane that has the maximum margin in an N-dimensional space (N — the number of features) that distinctly classifies the data points. Logistic Regression produces probabilistic values while SVM produces 1 or 0. So, LR makes not absolute prediction and it does not assume data is enough to give a final decision.

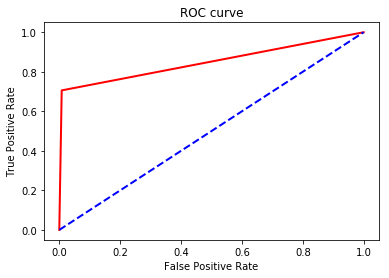
For our SVM classifier, we achieved similar results to logistic regression.

* Accuracy: 96.50% (93.01% - 99.30%)
* Sensitivity: 0.7059 (0.3333 - 0.9286)
* Specificity: 1.0 (0.9841 - 1.0)
* Confusion Matrix:

|  |  |  |  |
| --- | --- | --- | --- |
|  |  | Predicted Class | |
|  |  | Not Infected | Infected |
| Actual Class | Not Infected | 127 (120 - 134) | 0 (0 - 2) |
| Infected | 4 (1 - 9) | 10 (4 - 20) |

*Confusion Matrix for Support Vector Machine Model*

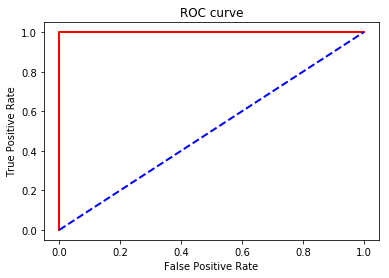
ROC Curve for SVM ( fig.4 ) : Area Under the Curve = 0.8490 (0.6667 - 0.9643)



*Fig.4. ROC curve for Support Vector Machine Model*

**2.2 Image Model**

For the model using features derived from the wound images, over 100 random trials, a median accuracy of 100% was obtained with values ranging from 99.296% to 100%. The model’s median sensitivity was 1 and all trials achieved a perfect sensitivity value, while its specificity was on average 1 with values ranging from 0.9922 to 1. The ROC curve is displayed in the figure below ( *Fig.5* ).



*Fig.5. ROC Curve showing results for the Image Model*

The median area under the ROC curve is1.0; the values ranged from 0.9961 to 1.0. On average, the L1 penalized model selected 25 features to use in classification, but this value ranged from 19 to 29 features since the program performed 100 iterations every time it ran. The features that were determined to be the most relevant by the model and their median coefficient values are given in the table below (*Table.3*). Since the image was divided into eight blocks ( 2 x columns, 4 x rows ), most of the features display the block number, attribute of the LAB color space and the mathematical quantity that it computes for that attribute.

|  |  |
| --- | --- |
| **Feature** | **Coefficient Value** |
| Color Histogram (Feature 74) | -0.60 ( -0.80 — -0.46 ) |
| Color Histogram (Feature 147) | -0.53 ( -0.60 — -0.47 ) |
| Block 6 L Mean | -0.26 ( -0.74 — -0.01 ) |
| Color Histogram (Feature 1) | 0.25 ( 0.15 — 0.42 ) |
| Block 7 L Mean | -0.23 ( -0.71 — -0.00 ) |
| Block 1 L Mean | -0.21 ( -0.72 — -0.01 ) |
| Block 3 L Mean | -0.19 ( -0.58 — -0.02 ) |
| Block 1 A Mean | -0.20 ( -0.65 — -0.01 ) |
| Block 5 L Mean | -0.16 ( -0.70 — -0.01 ) |
| Block 8 L Mean | -0.19 ( -0.70 — -0.01 ) |
| Color Histogram (Feature 65) | -0.19 ( -0.34 — -0.01 ) |
| Block 7 A Mean | -0.16 ( -0.67 — -0.00 ) |
| Block 6 A Mean | -0.16 ( -0.55 — -0.01 ) |
| Block 3 A Mean | -0.13 ( -0.61 — -0.00 ) |
| Color Histogram (Feature 73) | -0.17 ( -0.32 — -0.01 ) |
| Block 4 L Mean | -0.14 ( -0.60 — -0.00 ) |
| Block 2 A Mean | -0.14 ( -0.50 — -0.01 ) |
| Block 2 L Mean | -0.15 ( -0.52 — -0.00 ) |
| Block 5 A Mean | -0.13 ( -0.60 — -0.00 ) |
| Block 1 B Mean | -0.12 ( -0.46 — -0.00 ) |
| Block 3 B Mean | -0.10 ( -0.66 — -0.00 ) |
| Block 5 B Mean | -0.12 ( -0.65 — -0.00 ) |
| Block 6 B Mean | -0.10 ( -0.62 — -0.00 ) |
| Block 4 A Mean | -0.09 ( -0.65 — -0.00 ) |
| Block 7 B Mean | -0.09 ( -0.42 — -0.00 ) |
| Block 8 A Mean | -0.07 ( -0.51 - -0.00 ) |
| Block 4 B Mean | -0.10 ( -0.47 — -0.00 ) |
| Block 2 B Mean | -0.08 ( -0.28 — -0.00 ) |
| Block 8 B Mean | -0.06 ( -0.38 — -0.00 ) |

*Table.3. Coefficient Value table showing the most commonly used features while classifying the images.*

**2.3 Combined Model**

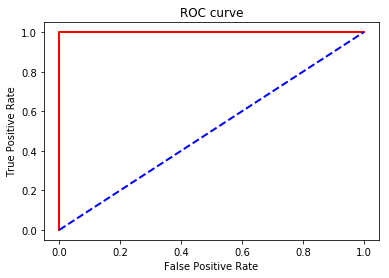
The evaluation metrics for our combined questionnaire and image model are as follows.

Accuracy: 100% (100% - 100%)

Sensitivity: 1.0 (1.0 - 1.0)

Specificity: 1.0 (1.0 - 1.0)

ROC curve:



*Fig.6. ROC Curve showing results for the Combined Model*

Area under ROC curve : 1.0 (1.0 - 1.0)

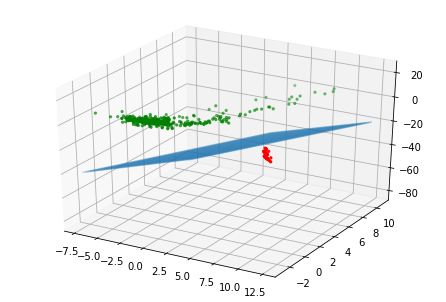
Number of selected features : 28 (22 - 31)

Feature relevance’s:

|  |  |
| --- | --- |
| **Feature** | **Coefficient Value** |
| Color Histogram (Feature 74) | -0.56 ( -0.73 — -0.40 ) |
| Color Histogram (Feature 147) | -0.48 ( -0.56 — -0.38 ) |
| Block 7 L Mean | -0.23 ( -0.66 — -0.01 ) |
| Block 6 L Mean | -0.22 ( -0.61 — -0.04 ) |
| Block 3 L Mean | -0.20 ( -0.72 — -0.01 ) |
| Block 1 L Mean | -0.20 ( -0.61 — -0.01 ) |
| Block 5 L Mean | -0.18 ( -0.70 — -0.02 ) |
| Color Histogram (Feature 1) | 0.21 ( 0.04 — 0.38 ) |
| Block 8 L Mean | -0.19 ( -0.51 — -0.01 ) |
| Block 1 A Mean | -0.16 ( -0.60 — -0.01 ) |
| Draining with Smell | 0.17 ( 0.07 — 0.38 ) |
| Draining color (Brown, Yellow, Green, White) | 0.17 ( 0.07 — 0.32 ) |
| Block 3 A Mean | -0.12 ( -0.75 — -0.00 ) |
| Color Histogram (Feature 73) | -0.17 ( -0.35 — -0.01 ) |
| Block 7 A Mean | -0.15 ( -0.58 — -0.00 ) |
| Block 4 L Mean | -0.12 ( -0.53 — -0.00 ) |
| Color Histogram (Feature 65) | -0.16 ( -0.29 — -0.01 ) |
| Block 6 A Mean | -0.10 ( -0.70 — -0.01 ) |
| Block 2 L Mean | -0.11 ( -0.37 — -0.00 ) |
| Block 1 B Mean | -0.11 ( -0.50 — -0.00) |
| Block 5 A Mean | -0.09 ( -0.50 — -0.00 ) |
| Block 2 A Mean | -0.10 ( -0.40 — -0.00 ) |
| Block 4 A Mean | -0.08 ( -0.51 — -0.00 ) |
| Block 5 B Mean | -0.10 ( -0.58 — -0.00 ) |
| Block 7 B Mean | -0.09 ( -0.48 — -0.00 ) |
| Block 3 B Mean | -0.06 ( -0.39 — -0.00 ) |
| Block 8 A Mean | -0.08 ( -0.37 — -0.00 ) |
| Block 6 B Mean | -0.07 ( -0.53 — -0.00 ) |
| Block 4 B Mean | -0.09 ( -0.67 — -0.00 ) |
| Block 2 B Mean | -0.06 ( -0.51 — -0.00 ) |
| Color Histogram (Feature 66) | -0.04 ( -0.22 — -0.01 ) |

*Table.4. Coefficient Value table showing the most commonly used features while classifying the combined data from the questionnaire and the images.*

The combined data model appears to classify the data perfectly. To further understand this, the dataset was constrained to include only the features that were most often determined to be relevant by the model. Since there were 28 features selected for this model it is possible to determine the Principal Component Analysis (PCA) along 28 different dimensions. To visualize the analysis, a 3-Dimensional representation was chosen along which the constrained data had the most variance. The following visualization of the data through this method was obtained.



*Fig.7. 3-Dimensional view of the Principal Component Analysis of the combined model.*

In *Fig.7,* the green data points represent uninfected patients while the red points correspond to patients with SSIs. It is seen that the two classes appear to be perfectly separable even in such a low-dimensional visualization. This explains why our model performs so well on the combined data, and indicates that, at least for the data we worked with, infection prediction can be accurately performed with just a few very salient features.

**3. Statistic Summary**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Model** | **Accuracy** | **Sensitivity** | **Specificity** | **ROC AUC** | **Features used** |
| GP Questionnaire | — | 0.952 | 0.833 | 0.8925 | **3** |
| Questionnaire with L1 | 95.80%  (92.31% - 100%) | 0.7134  (0.4545 - 1.0) | 0.9846  (0.9627 - 1.0) | 0.8529  (0.7235 - 1.0) | 9 |
| Questionnaire with L2 | 96.50%  (91.61% - 99.30%) | 0.75  (0.4118 - 0.9333) | 0.9921  (0.9615 - 1.0) | 0.8666  (0.7058 - 0.9666) | 13 |
| Questionnaire with SVM | 96.50%  (93.01% - 99.30%) | 0.7059  (0.3333 - 0.9286) | 1.0  (0.9841 - 1.0) | 0.8490  (0.6667 - 0.9643) | 13 |
| Images | 100%  (99.30% - 100%) | **1.0** | 1.0  (0.9922 - 1.0) | 1.0  (0.9961 - 1.0) | 25  (19 - 29) |
| Questionnaire + Images | **100%** | **1.0** | **1.0** | **1.0** | 28  (22 - 31) |

*Table.5. Combined data of all the different models used along with their Accuracy, Sensitivity and Specificity.*

**4. Further Advancements**

Our results indicate that using image data for SSI prediction is likely the best way forward. The features derived from the images proved most useful in obtaining accurate predictions and also, using images instead of questionnaire results bypasses the issue of patients inaccurately reporting answers. One potential method for improving the effectiveness of our model would be to improve the quality of the images, perhaps by standardizing their size, orientation, and other properties. This could be accomplished by multiple methods. One of the easiest way would be to capture images using a tripod stand and placing the camera in a position where all the images look similar. Also, another method that can be used is taking pictures in a standard sized frame or other object around the wounds that can be used as a reference to automatically digitally process input images. The most efficient technique that could be used to capture images is by using a thermal camera. This would help add a predictive value to each image.

There are significant advantages of a thermal imaging camera over normal cameras. The thermal camera allows to capture inviable heat radiations regardless of lighting conditions. Regular cameras that capture only visible light can be fooled, in some cases, by visual camouflage, or in situations where similar colors or patterns blend together. This can make objects or people that need to be detected unobservable. It was found that emissivity of wounds was similar or slightly higher to intact skin, with lower values at wound edges [6]. Hence it can be concluded that if image data is collected using thermal image camera it will give a significant difference in the number of features used and will also be more accurate

**5. Acknowledgement**

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