European Journal of Molecular & Clinical Medicine
ISSN 2515-8260 Volume 7, Issue 07, 2020

A Critical Review Of Various Methods For Timely Identification Of Post-Operative Infection

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Conflict of Interest: *None*
Funding: *NewGen Innovation and Entrepreneurship Development Centre, National Science and Technology Entrepreneurship Development Board (NSTEDB), Department of Science & Technology (DST), Government of India*

Abstract:
To detect and prognosticate the occurrences of post-surgery infections has now become an important requirement in the field of medical sciences. It helps in making the strategies for management of the infections thereby reducing the time of hospital stay and patient morbidity.

Classification of patients into high and low risk has effectively aided in leading a number of publication, researches as well as progress in the bioinformatics and biomedical field and for the study of various methods for timely identification of infection, application of Machine Learning techniques and neural networks. Among the collections of these techniques, including thresholding algorithms, Artificial Neural Networks (ANNs),machine learning algorithms usages of new technology are been used in research programs as it helps in developing predictive models with great resulting accuracy in decision making process. Being able to accurately calibrated surgical site infections (SSI) risk in medical field would be useful for two key reasons. First, it helps in determining the likelihood that a particular patient get the particular signs of surgical site infection which can be similar to the divided groups and useful in deciding the method of prevention. Second, an accuracy model/system will ease and forward the significant similarity and also

the comparison of (SSI) that is surgical site infection rates within health care providers and the facilities.

In the current paper, we have done a literature review of the emerging methods involved in the prediction of infection and detection of the same. These models are based on numerous unconfirmed and supervised techniques like neural networks, algorithms, thermal techniques, devices and machine learning (ML) techniques. As an emerging application of machine learning methods and thermal devices, we here describe the most up-to-date techniques used, researches made and publications referring post-operative infection models as the aim of their work which use these techniques.

Introduction:

Recently, there are other systems such as MRI and when an SSI occurs ,it is noticed that the patient's hospital stay increases by 60% by comparing it to non-infectious patients after surgery .Now a day's only after appearance of clinical signs and symptoms the SSI can be detected, but SSI goes it's advance stage so the patient needs medical care .And here more chances of patients can die. This infection can happen after the patients after getting discharge.

As the surgical site infection can be developed after the operation which cannot be seen by naked eyes. Bacteria is the main reason for SSI. After the surgery SSI develop 10 days to several weeks .If the treatment is not given then the infection spread in depth near to the surgery . Also ,it takes more time and efforts to treat the patient and as patients hospital stay increases the hospital money is also increases.

Screening in early stage, which aim is to find out which types of cancer is this before its clinical appearances. It is one of the method which tried by the scientists.

Now in present work, studies that use various methods for early detection of infection which includes using new technology, thermal images, neural network ML techniques for modeling infection related prediction model are available.

This paper mainly focuses on approaches made by the scientist and methods used/published for detection model of post-operative infection in following points-

- Approaches for detection.
- Methods for prediction model.
- Difference in output of each paper.

Approaches for Detection of Post-Operative Infection.

Many methods are given in the literature for the detection of post-operative infection. In cancer prognosis ML concept is used. Supervised and classification algorithm are used in most of the studies for the prediction. According to the analysis , the multidimensional non homogeneous data combination with the applications used in feature extraction ,selection and classification can provide as an effective tool for conclusion in the infection detection domain. The main motive of this techniques is to obtain a model which can useful to perform classification, prediction, estimation or any other similar task. [1]

In order to examine the capability of non-invasive infrared thermography (IRT), after surgery, to predict infection. [2]
From day 2 the thermal camera was used in hospital. Thermal images was taken of wound site and abdomen. In this paper, infrared camera is used for temperature detection.So, is used to capture patients for surgical site infection after the Nuss procedure .camera has the potential to monitoring the infection in many situations .[3]

Uses of infrared camera and also comparison between the temperature obtained by the thermal images and long infrared camera [2-10]

In this paper, it is to check the practicality of using thermal images to diagnose bacteria in alternate of a chest x-ray [4]. Following the aims of this study are:
1) To check by using a thermal camera it is possible to detect heat emitting areas from the chest it is the location which chest x-ray shows focal consolidation consistent.
2) To determine heat emitted from the chest is changes over time if possible to take serial images of chest.

The OCM (**Oncology Care Model)** is created by the Center for Medicare and Medicaid Innovation. It is is an episode-based payment system . The high-risk patients is identified by OCM [5].For example :in a 24-month of period, 1205 number of patients had operations for malignant disease.17.3% was rate of SSI. Six independent predictive risk factors are identified by multivariate stepwise logistic regression model in Machine learning : impure and infected operations, male sex, surgical duration greater than 280 minutes, prior radiotherapy, American Society of Anesthesiology class III to V, and antimicrobial prophylaxis not according to convention. Two groups of patients were identified, On the basis of individual risk scores-
(1) low risk score ≤8 , surgical site infection rate is 10%.
(2) High risk score ≥9 , surgical site infection rate is 33.6%.

The independent association of patient is determined by multivariate stepwise logistic regression and surgical predictor with the risk of infection within 30 days of surgery .All surgeries randomly divided which was recorded in the National Surgical Quality Improvement Program(NSQIP) from 2010 . They calculated the score of risk which have first three nos. are common in CPT in order to record or capture the factors which are specific to particular surgery[6] .
In this paper , MATLAB software and the Lasso or elastic net regularization for linear models in MATLAB for the prediction are used.4290 participants are recorded from July 2007 to December 2009 who had gastric surgery and entered in KNISS, Prediction of the emersion of SSI were analysed using lasso method. In order to get tuning parameter value Cross validation were applied [7].

1744 participants who underwent pancreatic, hepatobiliary, and colorectal resections at Johns Hopkins Hospital were analysed. Here by using multivariable logistic regression risk factors for any patient SSI were examined[8] .

In this , 145 participants who had t intestinal perforation, abdominal at two hospitals. Higher risk of infection was related with a larger number of injured organs, injury to the left colon necessitating colostomy, increased age, larger number of units of blood were shown by Logistic-regression analysis [9] .

For the prediction of the infection/disease in different body parts logistic regression is used [9-11]. In logistic-regression. :It analyze unadjusted association of 30-day post discharge. Multi variable logistic regression model was then the criterion taken to assess variables which are related with risk of post-operative infection [13-14].

In order to detect postoperative infections at early stage C reactive protein levels may b useful. Diagnostic and time-critical recommendations values were analysed for CRP use as an infection indicator. CRP was one of the variable of severity was accepted for clinical disorder . CRP is nothing but it can use marking of damage tissue in addition to inflammation [15].

In order to predicting the deep wound infections after thoracolumbar surgery using pedicle screws they examine the postoperative suction drainage tip cultures as a method . Analyse the results of cultures on postoperative suction drainage tips from a 471 cases of surgery. Determine the specificity ,predictive value, sensitivity . And examine the confined bacillus. Calculable analyses of serum CRP is performed with the help of Turbidimetry[16].

In this paper, To examine the use fluoro-D-glucose as a detecting infection, rabbit osteomyelitis model was used in condition of post-operative inflammation. Analysis was performed on the basis of standardized uptake value (SUV) at surgical site[17].
In order to detect the infection there types immunologic methods such as ELISAs, immunological assays, solid-state radioimmunoassay, and immunofluorescent assays are available for detection. However, for detection of infections need a lab and expert to perform the assays .And there is to perform immunological assays for the biological samples which are not easy to obtained from an animal. They are expansive as well. Until clinical symptoms are appear clearly can't perform this. So there is a need of diagnostic technique for the early detection of infections which should be simple, rapid, non-invasive and inexpensive [18].

3. Methods for Prediction Model.

1.Infrared Thermal Camera and Thermal Imaging

Early inflammatory changes like “calor” (increased heat) could be useful in identifying SSIs in subclinical stage. Thermal imaging of surgical site can detect rise in temperature (related to inflammation) even before appearance of clinical signs and symptoms.
1. The featuring data ,including maximum temperature according to, linked to infection or inflammation, and temperature of normal healing wounds can be collected also recorded using the Long-wave infrared thermography. The aim of this was to induce whether a wide or

slight change in temperature of wound associate with post-operative infection can be detected by the long-wave infrared thermography (LWIT, or thermal imaging) camera. Also whether long-wave infrared camera can be used to detect the Surgical site infection and inflammation as and compare it with the normal temperature of the patients with similar wound locations with respect to the particular kind of surgical operation and location [19].

In this method, the relative maximum temperatures which are observed ,collected and recorded by thermal camera and digital thermal imaging. The authors validated and exposed the use of thermal digital cameras and dual-imaging infrared to analyse images . In the two case which were classified with medically diagnosed wound infection, an temperature elevation was witnessed with temperature maximums differences comparing the temperature of wound and healthy skin which is calculated to be 4-5° wth the help of longwave infrared camera . Also it was able to record the relate change of temperature of +1.5° C to 2.2° C in patents having SSI of infection [20].

2.[a]Collect an thermographic image of structure of the infected site
[b]After that ,determine the mean temperatures of the infrared thermographic images and classify them according.
[c]Finally, detection of early or subclinical infection and infection(along with temperature values) of particular anatomical structure where the mean temperature change of a structure is probably less than 1° C. in comparison to the mean temperature of the same structure of the same Species which can be obtained using the infrared thermographic images of same structure with same location without infection and inflammation taken by the thermal camera Another way,

[d] To determine the total mean temperature of the symmetrical anatomical structure's using infrared thermographic images; and

[e] Finally, inflammation can be detected of an structure by comparing the total temperature of infected structure (which is be greater in case of infection) with the predetermined temperature of non-infected structure of same species.

2.Machine Learning Algorithms

Use of new trending technologies like Machine learning which is a essential and basis of IOT are now a powerful ,popular tool for clinical, medical field researches and researcher. These techniques can facilitate and record the relationship patterns , Also they are able to facilitate the effective future prediction of any feature in complex database too .

Machine learning techniques like Decision Trees (DTs),Artificial Neural Networks (ANNs),Support Vector Machines (SVMs) and Bayesian Networks (BNs), which are used and variety of trending tech have been used various researches for the modelling of infection predictive models, which results increase in accuracy of prediction ,decision making models . From these technologies machine learning ,an essential component of IOT, is related to the data analysis and data sampling [17], There are two phases in learnng process: (i) Creating a fundamental ,prerequisite dataset and determination of dependencies in a given complex or simple dataset , (ii)using these approximated dependencies for the prediction of output values.

ML has been accepted as one of the best approaches for prediction in medical .There are total two types of algorithms in ML (i)unsupervised learning and (ii)supervised learning , these are the two primary types of machine learning technique. In supervised learning, the desired output is already known before the prediction Contradictory, in the unsupervised methods, the desired output unknown before the prediction,

Bayesian Networks (BN Classifier)

A probabilistic graphical model which represents set of data with associated known dependencies with DAG that ie Directed Acyclic Graph creates a statistical Bayesian network model also known as Decision Network, Belief Network, Bayes (Ian) model .In this BN ,when an event occurs , even the least possible event of several events is taken into consideration for prediction of the model.

Probabilities are calculated and not the prediction .according to the name of this model ,knowledge coupled are represented according to its calculated probabilities in an DAG . Its applicable and used widely to in the events many task related to classification and representation of knowledge coupled probabilistic dependencies need to understand.

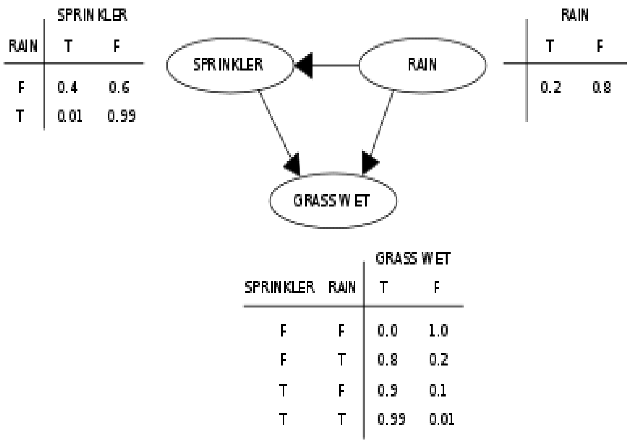

Fig 1: An illustration of a *Bayesian Networks*. Different nodes such as Sprinkler , rain and Grass wet and there probabilities which have been calculated in particular table. Accuracy of model with the neural network is up to:69%

SUPPORT-VECTOR NETWORKS (Svm)

Support vector machine (SVM) which comes under the supervised algorithm analyze the data used for regression as well as classification analysis

Svm is used as classification and regression model for analyzing and predicting data. The models learn with the training data set and the testing data will be classified as per the belonging of data according to class that ie the groups separated by the gap.

In support vector machine, the points are mapped in a space where the input data are categorized and mapped into different parts separated by a clear gap. The gap is made as wide as possible. New testing and training data mapped into categories divided by wide gap and in same space and predict which category it belongs as per the sides of gap.

Support vector machines are a more modernistic , accepted , approved ML methods which can be used in many fields such as medical field or problems based on predictive models in particular site infection.

SVM is a supervised learning method that classifies at data and sorts it into one of the two categories Initially , SVM identify the hyperplane in a space which separates the input data values into sides of the gap that ie the classes. The next data will be places in the same space depending upon the classification based on where the data lies in that space.

The distance between the nearest instance with the gap can be increased so as to get more accurate result.

The probabilistic outputs was obtained for SVMs Fig. 2 illustrates how an SVM works .The decision boundary between the two clusters is the identified hyperplane in SVM obviously used for the detection of any misclassification .

SVM gives more accuracy .

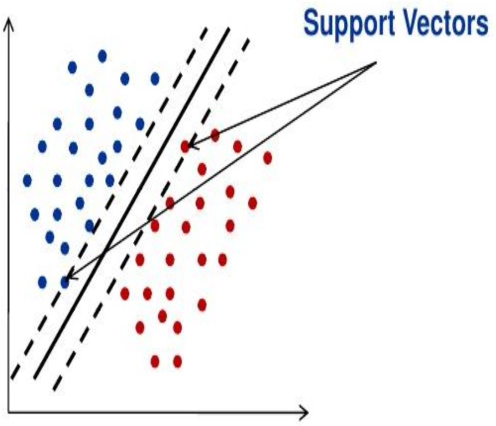

Fig. 2. A Image of Simplified working algorithm Svm. In figure the blue and red category is classifies by the gap as shown in figure. Accuracy of model with the neural network is upto:71.0%

DECISION TREE (DT)[21]

Decision Tree(DT) Analysis which is not only used for supervised learning algorithm but also for unsupervised learning, like clustering. It is an predictive modeling tool having vast applications in different fields. A DT is developed in an in-sighted and algorithmic way which splits the dataset based on conditions. The is the hierarchical way with tree model having branches and splitting up the data values .

A tree like structure for classification is constructed by decision tree .Here like a flowchart there are nodes as input values and takes decisions splitting the data set according. DTs are among the ones which were developed earliest and are more efficient accurate machine learning model used for regression and classification as well. Because of the tree-structure of DT , they are easily understood , interpreted and easy to learn and apply. When a new data is added for classification ,the model will classify and place it to desired place or predicted place according to its class. The output of this method is decided after the definite architectural reasoning condition which makes it most appealing technique.

Fig shows the working of an program with DT algorithm.

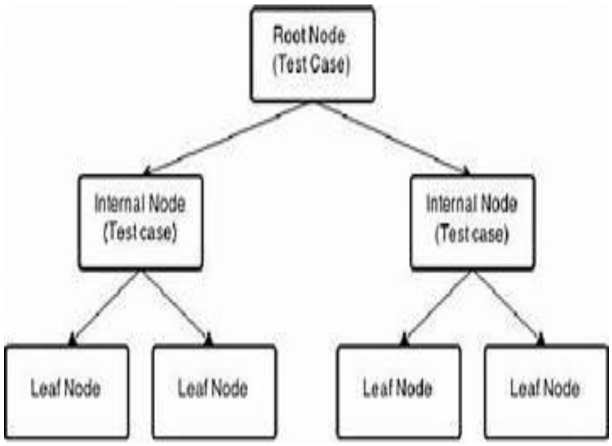

Fig 3: DT structure is illustrated where the primary node is root node having child nodes called as Leaf Nodes

Accuracy of model with the neural network is up to:93.0%

NEURAL NETWORK[22]

Neural networks are especially used for the pattern recognition for identification and classification of signals such as vision, speech, that is audio, video and control systems. NN can also be used for the training and understanding the pattern of the input data. Time-series modelling as well as prediction can be done with the ANN .
A neural network is structure with layers which resembles the neurons in the brain, (having network structure) with structured layers of nodes connected with arrows. A neural network is able to train itself by learn the data from given dataset ,because of which it is used for training the machine for the applications like recognizing patterns, classifying data, and forecasting future events with high accuracy for tested prediction.
ANN contents many layers of abstraction including one input layer , many hidden layers(one or more) and one output layer. The more the merrier can suit here for hidden layers. A neural

network can be trained for the pattern recognition in voice and visual sources. Ann works with input values and weights and its connection with each nodes. The automatic adjustment of weights according to the input data and learning algorithm in training set till the neural network predicts the desired task correctly be the advantage of neural network.

In neural network, the features and parameters will train the machine and help in prediction model and predict the output with great accuracy. Accuracy of model with the neural network is up to: 96.5% which is most desirable.
In this figure , there are many data inputs and the hidden layers for the pattern recognition and the output layer.

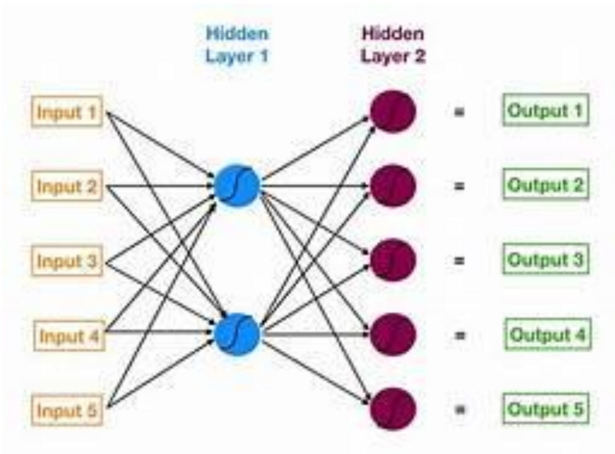

Fig. 4 An working of the neural network structure. The output of one of the nodes is connected via arrow to the input of another node..

LOGISTIC-REGRESSION

Logistic Regression is Classification and an supervised training algorithm -
This model combines decision tree and LR learning. In logistic regression ,it categorizes data as discrete ,unique classes with training and testing relationship from a given set of known data i.e. supersized data. Logistic regression creates a linear relationship from the dataset on which it is applied and then it introduces a non-linearity with a sigmoid function.LR uses an equation as the representation, just like in linear regression.

Input values which is x in this expression is a combination of linear data which use weights or the coefficients beta as referred in for this prediction of y which is and output value .
Logistic regression differs from linear regression by this primary and important key that that the output for this model is a (0 or 1) that is binary values rather than a numeric value.
Logistic regression equation is as follows:

$$Y = e \wedge (\beta 0 + \beta 1 * x) \div (1 + e \wedge (\beta 0 + \beta 1 * x))$$

Where ,
Y is predicted output of model,
$\beta 0$ is the intercept term ,

$\beta 1$ is the coefficient value for each single input value x . Each column in the input data it has an associated beta β a constant real coefficient value which the model learns in training.

LR is similar to linear regression method, but the difference is that the logistic use the logistic function and sigmoid function for predictions to be transformed. Because of this ,we no longer learn the predictions as a linear combination inputs as in we did with linear regression,

Continuing the equation, the model equation can be changed as stated below:

$$p(X) = (e \wedge (\beta 0 + \beta 1 * X) \div (1 + e \wedge (\beta 0 + \beta 1 * X))$$

$$(p(X) \div 1 - p(X)) = (\beta 0 + \beta 1 * X)$$

The calculation of the on the right is linear again (just like linear regression), and on the left(input) is given as log of the probability of the default class.

The right sides , calculated output is observed similar to linear regression and on the left side , log of probability of the default class is shown. The given graph makes logistic regression an useful ML algorithm.

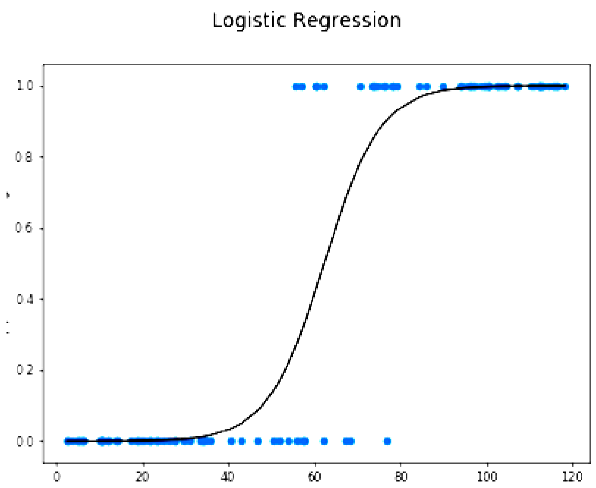

Fig:5 Illustration Of The Logistic Regression Output Graph

According to the recent Pub Med results regarding the subject of ML-

For nearly three decades the ML techniques like neural network (ANN) and Decision Tree(DT) were used in detection modelling. Regarding the subject of ML , many surveys have been carries out. From a recent survey from Pub Med regarding the same .the wide majority of these techniques and publications apply one, two or more ML algorithms such as DT,ANN, classifiers and integrates data from various websites ,hospitals or sources for the detection of infection of cancer and tumors .

In growing trend of using IOT and new technologies in medical research , use of neural network and ML algorithms like SVM, DTs , Logical regression , BN etc are used in development of prediction model with incremental accuracy.

3.LASSO METHODOLOGY[23]

Lasso (Least Absolute Shrinkage And Selection Operator; also lasso or LASSO) which is included in ML and statistics is used for regression analysis. Lasso performs both variable selection as well as the regularization which enhances the prediction accuracy of the model.
As with the model building on lasso problems can produce a good calibrated prediction model for risk prediction of various infection such as post-operative in cancer, tumor or gastric ,etc ,it has an advantage over logistic regression.

A wide variety of objective functions including M-estimators in general, generalized estimating equations, generalized linear models , and proportional hazards models, in the obvious way are available in Lasso regression method . The objective function $\frac{1}{N}\sum_{i=1}^{N} f(xi, yi, \alpha, \beta)$

Is that it estimates the solution to where only β is penalized and α will be free to take any allowed values and also $\beta 0$ is not penalized in basic case.

$$\min_{\alpha,\beta} \frac{1}{N}\sum_{i=1}^{N} f(xi, yi, \alpha, \beta) \text{ subject to}$$
$$\|\beta\| \vee 1 \le t$$

4. C-Reactive Protein (*CRP)*

C-Reactive Protein (CRP) , discovered in serum of Francis and Tillett . CRP was discovered for the cause of disease called pneumonia in year 1930 is an acute-phase reactant. Also at early time crp was considered as a vital parameter for severity for various diseases. CRP not only indicates the damages tissues but also indicates the inflammation. The CRP level might prove useful for early detection of post-operative infection.
It is observed that CRP indicates the humeral response of immune system In this method , it not only analysis the time-dependent reference and baseline values for the use of crp in postoperative but also calculates the predictive value, sensitivity . CRP analyses and calculates the specificity and investigated the isolated pathogens. The C-reactive protein can be used for quantitative analysis using Turbidimetry.
Need of technology is evident from GBD studies around the world[24-28]. Many studies concerned to infections and related factors were reported[29-36].

Sr.no	**Name of paper**	**Year of publication**	**Technology Enabled**	**Limitations**
1.	Risk index for prediction of surgical site infection after oncology operations	1998	Logistic-regression on oncology operations	1.Less Database was used so accuracy is less 2. Used pre-infection and physical features such as sex, habits.
2.	Early detection of inflammation and infection using infrared thermography	2003	Infrared thermography	1. No statistically changes in parameter measures of disease before 10 days of post infection. 2. It requires medical expert
3.	Usefulness of procalcitonin in early detection of infection after thoracic surgery.	2005	Procalcito and crp (C-REACTIVE protein Parameters used for prediction	1.It requires laboratory 2. It requires medical expert, layman alone won't be able to perform. 3. Complex and time consuming process.
4.	Monitoring for Deep Wound Infection after Thoracolumbar Surger	2006	C-reactive proteins based prediction model	1. It requires laboratory 2. It requires medical expert, layman alone won't be able to perform. 3. Complex and time consuming process
5.	Assessment of the Accuracy of Procalcitonin to Diagnose Postoperative Infection after Cardiac Surgery	2007	Procalcitonin is the main feature on which prediction has been made	1.Laboratory test is required 2. Time consuming, not efficient. 3. Medical expert required.

6.	C-reactive protein levels for early detection of postoperative infection after fracture surgery in 787 patients	2009	C-reactive proteins based prediction model	1.It is time consuming 2. less data base , accuracy is less 3. it is not automated
7.	Usefulness of Infrared Thermal Imaging Camera for Screening of Postoperative Surgical Site Infection after the Nuss Procedure	2013	Infrared Thermal Images and thermography	1. The hot spot which appears in the image, may show the healing process, accuracy may vary and predict wrong answer.
8.	Gastric Surgical Site Infection Risk Prediction Model	2015	Lasso method	1. Based on physical features. 2. Time consuming
9.	Thermographic mapping of the abdomen in healthy subjects and patients after enterostoma	2015	Thermal Images and thermography	1. A pilot Study so has limitations 2. Limited to color related Images.
10.	Prediction of Surgical site infection after hospital discharge in patients undergoing major vascular surgery.	2015	Logistic Regression	1.Fails to compare the infection with time for each patient 2. Time consuming.

11.	Machine learning applications in cancer prognosis and prediction	2015	Bayesian Networks (BNs), Decision Trees (DTs) ,Neural Networks (ANNs) and SVM	1. Accuracy varies with the algorithm 2. Database has to create in specific order.
12.	Risk factors and prediction model for inpatient surgical site infection after major abdominal surgery	2017	logistic-regression	1. Age factor is considered as the main parameter which can consider un related parameters affecting the prediction model
13.	Thermal Imaging to Diagnose and Monitor Suspected Bacterial Infections	2017	Thermal images and thermography FLIR device	1. Flir device is required 2. The output depends on temperature value which may disguise the answer as the healing temperature can get added.
14.	The surgical wound in infrared: Thermographic profiles and early stage test-accuracy to predict surgical site infection in obese women during the first 30 days after caesarean section.	2019	Thermal images and thermography	1. Laboratory is required . 2. Only medical Expert can handle the project 3. Time consuming

Table 1: Difference in output of each paper.

- **Table 2 : Analysis of Methodology**

SR.No	Methodology	Advantages	Limitations
1	Thermography	Accuracy is high, infection can be visualized.	Thermal camera is required which is costlier.
2	Lasso method	Accuracy is more the logistic regression and easy to implement	Laboratory is needed, not used in modern technology, time consuming
3	BN	Accuracy is upto 69%	Data base need to be created with neat specifications , accuracy depends on training data.
4	SVM	Accuracy is upto 71%	Data base need to be created with neat specifications , accuracy depends on training data.
5	Decision Tree	Accuracy is upto 93%	Data base need to be created with neat specifications , Accuracy depends on training data.
6	Logistic-regression	Accuracy is upto 96.5%	Data base need to be created with neat specifications , Accuracy depends on training data.
7	Neural Network	Accurately is high even when database is not big, Easier to use.	Accuracy depends on training data.
8	Thermal Images and Flir device	Accuracy is higher.	The output depends on temperature value which may disguise the answer as the healing temperature can get added.

Conclusion

In this paper, a comprehensive review of Methods for early detection of post-operative infection including brief explanation of use of Thermal Images that is thermography, Neural network, Threshold Algorithm , Machine learning algorithmic such as BN, Support-vector machine(SVM),Decision tree , Neural network, and different methods such as lasso etc with the accuracy and the limitations.
In our project some of the limitations such as time consuming is retarded and it is an efficient, fast and accurate system where a layman can use without guidance the expert person every time.

It is portable and can be used in rural areas , resulting in less hospital stay ,less cost and less suffering to patient helping doctors for detection and diagnoses this project will primarily focus on the prediction of probability of having infection also if infection is present or not and if present how much and difference from previous image and predict the output of next image so that it can be used in future in place of MRI.

'A non-contact system for early detection of post-operative infection'. Also it is useful for continuous monitoring. It helps us to achieve continuous measurement of vital sign parameters during the whole day without limiting the patient mobility. To analyze vital sign parameters for disease diagnosis to assist professionals. This application will be easily available and can be used with smart phones which almost everyone has. It can be easily transportable from one place to another. It can be affordable at low cost and less maintenance.

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