ECTOPIC PREGNANCY INCIDENCES AND INFLUENCE OF SOFTWARE STRATEGIES IN THE PROPHECY

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ABSTRACT:

Ectopic pregnancy cases increases the jeopardy factor in females during prenatal period which also raises the view of diagnosis for prior detection and cure. These are differentiating into variety of forms day by day, making many challenges to the diagnostic practices. Accordingly, this medical field is also getting more attention and influenced by software revolution in present scenario to a greater extend. There are much software techniques available in the market for diagnosis. More evolutions of techniques in this field are on the foray with the advancements in many software techniques and tactics. There are many conventional and custom based software available in the market for the judgment and result analysis in EP cases. The limits of the available method extend with respect to particulars like sensitivity, accuracy, image reading, compatibility etc. This research paper is a brief literature that reveals the ectopic pregnancy circumstances and the investigation protocols followed by the impact of software.

Keywords: Ectopic pregnancy, Deep Learning, ANN, SVM, beta-hcG

INTRODUCTION:

Ectopic pregnancy is the term utilized to define a pregnancy that develops outside the uterus. Ectopic pregnancies are a main cause of morbidity and mortality on a global scale. Ectopic pregnancies most frequently occur in the fallopian tubes. The fallopian tube is where ectopic pregnancies occur at a high incidence. It may rupture if overstressed by the developing pregnancy; Ruptured ectopic pregnancy is the medical term for this situation. Internal bleeding, infection, and in specific cases death may result from this. Ectopic pregnancies are becoming more and more transient, putting women at danger. Early diagnosis and treatment are preferred because this illness may also be life-threatening.

Historically, the diagnosis of EP was made at the time of operation before the widespread use of regular ultrasound. Before 1970, about 50% of patients exhibited with shock and more than 80% of EPs were diagnosed after rupture. As a result, practically all women underwent surgery as soon as the diagnosis was made, going immediately to the operating theatre. In 1883, Tait published the first account of a successful surgical cure for EP. In 1973, Shapiro outlined care with laparoscopy, which is today the accepted surgical technique. Laparoscopy has long been regarded as the definitive method for diagnosing EP. Surgery alone cannot provide a diagnosis with 100% sensitivity. While some EPs may not be detectable by laparoscopy because they are too small to be seen in the Fallopian tube, others may be self-limiting and never be spotted during laparoscopy. There could have also been erroneous laparoscopic findings, both good and negative. The detection of an ectopic pregnancy is now considerably easier thanks to the development of ultrasound sonography and hCG quantifications. As a possible reason for mortality in some first-trimester cases. [2]

TVS is currently posing a diagnostic challenge to laparoscopy, the gold standard for the diagnosis of EP. More than 80% of EPs are now found before rupture thanks to the earlier obtainability of high resolution TVS, and the US alone diagnoses more than 50% of asymptomatic women with EPs. An expanded selection of conservative treatment options, such as medicinal (methotrexate (MTX)) management and a "wait and see" expectant approach are made possible by earlier diagnosis in clinically stable women. In fact, non-surgical therapy management techniques have undergone a revolution thanks to the adoption of high resolution transvaginal ultrasound technology. Long-term research has shown that a number of ectopic pregnancies will naturally end. The necessity for surgical treatments like laparoscopy and unnecessary D&C, as well as morbidity from anaesthesia, surgery, and blood transfusion, can be minimised with proper selection of women for prenatal care. To ensure safety without sacrificing care, certain selection criteria must be followed when choosing women for expectant management. Thus, the necessity for surgery and its associated dangers is diminished. Surgery, however, should never be postponed in a patient with hemodynamic instability [1].

The mortality rates are on rising trend in the belongings of ectopic pregnancies. One of the main aspects is to find most suitable treatment and the other one is to diagnosis at initial stage. After the diagnosis, the forward challenge is the surgical treatment. The surgical treatment can be conventional or high sophisticated depending upon the category of ectopic pregnancy.

ECTOPIC PREGNANCY FACTS:

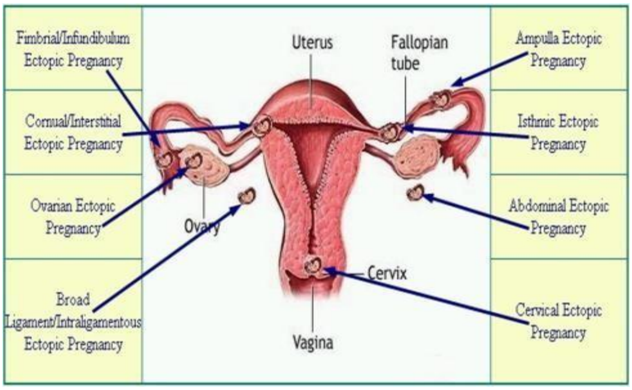
95% of ectopic pregnancies happen in the fallopian tube, with 70% occurring in the ampullary portion, 12% occurring in the isthmic portion, 11% occurring at the fimbriated end, and 2% to 4% occurring in the interstitial portion. Additionally, even when the fallopian tubes are morphologically normal, ectopic pregnancy is more common in women who used assisted reproductive technology, particularly after in vitro fertilisation. Inadvertent direct insertion of embryos into a damaged tube during embryo transfer can lead to tubal pregnancies. It also happens that a transferred embryo will go backward from the uterus into an abdominal tube. Due to the high prevalence of tubal damage, the use of ovulation induction treatment, and many embryo transfers that put the patients at risk for heterotopic implantations, IVF patients are more likely to experience an ectopic pregnancy. The chance of an ectopic pregnancy increases by a factor of 2.5 when an intrauterine device (IUD) is present. IUD use in the past may also slightly raise the chance of ectopic pregnancy. Ectopic pregnancies are thought to occur in 25% to 50% of pregnancies that are conceived with an IUD in place. Infertility appears to be a risk factor in general. There is no evidence to support a direct connection between ectopic pregnancy and the utilize of oral contraceptives, prior elective abortion, or spontaneous abortion. [3]

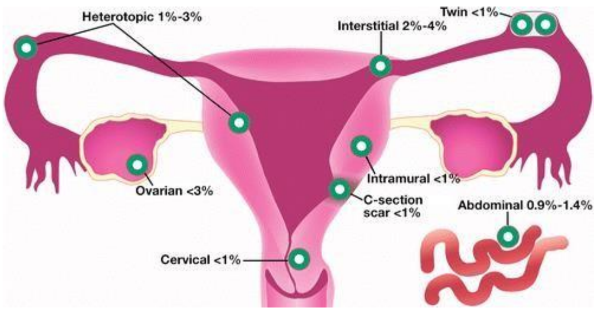
Transvaginal ultrasonography is used to diagnose unruptured ectopic pregnancy, as is the measurement of serum beta-hcG levels. Other type of sonography is pelvic sonograhpy which is performed in transverse and sagittal planes of trans-abdominal and trans-vaginal. In transvaginal sonography the image visualization can be improved inside the area where sonograph is carried out i.e., endometrial cavity and gestational sac.

The adnexa of the uterus are depicted clearly in pelvic sonography. The use of colour and Doppler methods is crucial for ectopic pregnancy diagnosis. In the colour Doppler images, the vascular ring in the ovary is a symptom that is extremely helpful in the diagnosis, though not in the identification of an ectopic pregnancy. A gestational sac in the uterus during ultrasound is useful for pregnancy diagnosis but will not be helpful for tubal pregnancy diagnosis.

Otherwise the gestational sac and fetal in ultrasound diagnosis is the presence of fallopian tube. This fallopian tube shows the results as ectopic pregnancy. During the ultrasound of transvaginal the hGC level above 1500 shows no gestational sac. This further demonstrates the presence of ectopic pregnancies. (By the time the hCG reaches 6,500, the sac should be discernible on abdominal ultrasound.

The doctor may advise methotrexate treatment to end the pregnancy if the pregnancy is confirmed to be ectopic but there is no evidence of rupture, or monitoring the hCG levels if the pregnancy appears to be on the verge of terminating naturally. Surgery to stop the pregnancy may be explored as a therapeutic option if the doctor believes there is a high danger that the ectopic pregnancy will break the fallopian tube. [16]





Adapted from www.ectopicpregnancyfoundation.org

Tubal pregnancy:

The fallopian tube, namely the ampulla, is the site of an ectopic pregnancy in over 95% of instances.The embyro outside endometrium shows the exact view during the magnification of images. Even adnexal form discrete from ovar also reveals precise indications. While performing trans abdominal ultrasonography, this mass can also be distinguished from an adnexal mass by pressing on the transducer, which will push the mass away from the ovary. During transvaginal sonography, the adnexal mass can also be identified from the ovary by pushing it with one hand while operating the scanner with the other. A hyper echoic ring enclosing an extrauterine gestational sac is referred to as the tubal ring indication in tubal pregnancy.

Interstitial pregnancy:

Less frequently occurring (2%–4% of cases), blastocyst implantation in the myometrial regions of the fallopian tube is the cause of ectopic pregnancy. Pelvic Inflammatory Disease (PID), past salpingectomy, and in vitro fertilisation are danger factors. In the myometrial part of the fallopian tube, the gestational sac can be seen eccentrically on sonograms. It is encircled by a myometrium layer that is just <5 mm thick. The interstitial line sign, a specific marker of interstitial pregnancy, is an echogenic line that surrounds the intramural region of the gestational sac and continues into the upper section of the uterine horn.

Cervical pregnancy:

Ectopic pregnancy in the cervix is a relatively uncommon form (<1%). Due to the risk of a life-threatening haemorrhage if dilatation and curettage is tried, it is crucial to identify this type. The cervical canal's gestational sac gives the uterus its hourglass shape. The hypervascular trophoblastic ring is visible on colour Doppler imaging. The main difference between cervical ectopic pregnancy and other pregnancies is continuous abortion with a gestational sac inside the cervical canal. Because there is no trophoblastic tissue surrounding the gestational sac that is aborting and forms the basis of the sliding sign, there is no hypervascular trophoblastic ring enclosing the active abortion. Because there is no trophoblastic tissue surrounding the gestational sac that is aborting and forms the basis of the sliding sign, there is no hypervascular trophoblastic ring enclosing the active miscarriage.

Ovarian pregnancy:

When the ovum is fertilised in the distal fallopian tube and then implanted in the ovary, ovarian pregnancy results. It is uncommon, making up about 1% to 3% of ectopic pregnancies. It has a close connection to PID and intrauterine device use. A gestational sac is visible in the ovary on ultrasonographyA living foetus is incredibly uncommon to observe. It needs to be carefully distinguished from corpus luteal cysts, which are significantly more frequent than ovarian ectopics. The ectopic gestational sac's wall is thicker and more hypoechoic than the wall of the corpus luteal cyst. Follow-up ultrasound imaging may reveal advancing involution and growing crenulation of the margins if the patient is stable.

Cesarean scar pregnancy:

The gestational sac is entrenched in the scar tissue from a caesarean section, which is an uncommon kind (<1% of instances). If the scar from a caesarean section does not heal properly, it may thin out in certain places where the gestational sac could implant. It might lead to uterine rupture and a bleeding that is fatal. The gestation sac can be observed on ultrasound near the scar from the caesarean section at the anterior inferior margin of the uterine cavity. To show the link between the gestational sac and the scar from the caesarean surgery, it is crucial to obtain a sagittal image. MRI can be employed in complex situations where the link between the gestational sac and the scar from a caesarean section is unclear.

Secondary abdominal pregnancy:

This type of ectopic pregnancy, which occurs in 0.9% to 1.4% of cases, may go unnoticed for a long period after the gestational age has passed. It happens when the gestational sac is placed in the abdominal cavity outside of the uterus, fallopian tubes, and ovaries. On omentum, vital organs, or major vessels, implantation may take place. On an ultrasound, the placenta and foetus are seen outside the uterus. Near the abdomen wall of the mother, foetal components are visible. MRI is very useful for locating the placenta and determining where it adheres to important organs.

Heterotopic pregnancy:

When both extrauterine and intrauterine pregnancy is present at the same time, it happens. With assisted reproductive technologies, it occurs more frequently (1%–3%). The corpus luteal cyst and intrauterine pregnancy are alternative diagnosis. Because β-hCG levels and doubling time are usual in heterotopic pregnancy, unlike other ectopic pregnancies, these pregnancies are problematic to diagnose. Laser ectopic pregnancy ablation or laparoscopic removal are two treatments for heterotopic pregnancy.

SOFTWARE USAGE:

The use of algorithms in computing to address issues in an intelligent manner is known as artificial intelligence (AI). It is a group of technologies that enables us to glean information from enormous amounts of data. Machine learning, a subset of AI, influences and more precisely defines it. ML analyses data using computer algorithms and then decides what to do after learning new information. Both organised and unstructured data types can be used in ML. The healthcare industry has benefited the most from AI, particularly for diagnosis and result analysis.

Artificial neural network:

Neural networks are influenced by biological neural networks even though they function extremely differently. It is made up of a network of neurons, which are tiny computing units that process information and learn to make decisions over time. One of the ANN algorithms is multilayer preceptrons. The fundamental traits of multilayer perceptrons are:

- The model features a differentiable nonlinear activation function for each neuron in the network.
- Input and output nodes cannot observe one or more tiers of the network.
- The extent of the network's high degree of connectivity is strong-minded by its synaptic weights.

However, these equal qualities are also to blame for the gaps in our understanding of the network behaviour. First off, it is challenging to do a theoretical study of a multilayer perceptron due to the existence of a dispersed type of nonlinearity and the maximum degree of network connectedness.

Second, it is more difficult to visualise the learning process when concealed neurons are used. The hidden neurons' representation of the features of the input pattern must be determined implicitly by the learning process. The decision-making process between several representations of the input pattern and the need to conduct the search in a considerably bigger set of potential functions make the learning process more difficult.

The back-propagation algorithm, which is a typical technique for training multilayer perceptron's, is a general case of the LMS algorithm. There are two stages to the training:

1) During the forward phase, while the network's synaptic weights are fixed, the input signal travels through the network layer by layer until it reaches the output. As a result, during this stage, changes are constrained to the neuronal network's activation potentials and outputs.

2) In the reverse phase, an error signal is generated by contrasting the network's output with the anticipated outcome. Layer by layer, the resulting erroneous signal is spread through the network, except this time the propagation is carried out backwards. In this second stage, the network's synaptic weights are gradually altered. Calculating the changes for the output layer is simple, but for the hidden layers it is considerably more difficult.

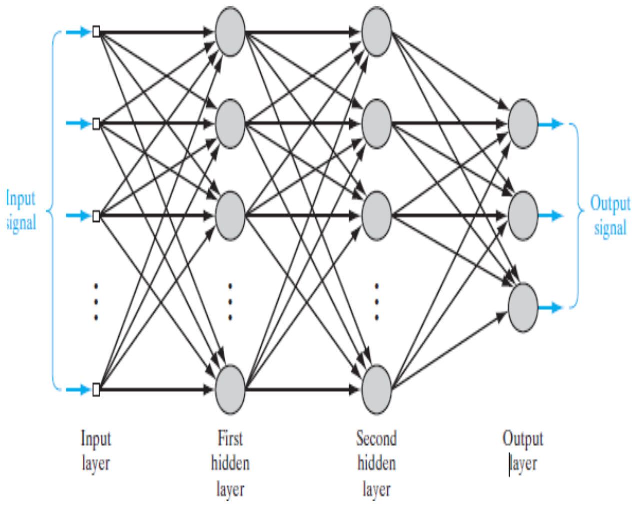


Figure shows the multi-player perceptron's structural graph, which includes one output layer and two hidden layers.

This network is fully connected to set the stage for an explanation of the multilayer perceptron. This implies that every neuron (node) in the layer before it is connected to every other neuron in the network. The network's signal flow proceeds layer by layer, in a forward direction, from left to right. The output layer of the network is made up of the output neurons. The network's leftover neurons make up its hidden levels. The hidden units are therefore not included in the network's output or input, which is why they are given the name "hidden." The input layer, which is made up of sensory units (source nodes), feeds the first hidden layer, which then applies its outputs to the second hidden layer and so on for the rest of the network. A multilayer perceptron's hidden or output neurons are built to carry out the following two computations:

1) Calculating the continuous nonlinear function of the input signal and specific synaptic weights for each neuron, which expresses the function signal that arises at each neuron's output.
2) The computation of an approximation of the gradient vector (i.e., the gradients of the error

surface with respect to the weights connected to the inputs of a neuron), which is required for the backward pass through the network.

Similar mappings like the ones we have learned have been learned using auto-associative MLP networks. The generative model and its inversion are both learned concurrently but independently, ignoring the connections between the models. As a result, learning proceeds much more slowly than it would in the present situation, in which the inversion is characterised as a gradient descent process.

Probabilistic Neural Networks (PNN):

A Radial Basis Function (RBF) network called a probabilistic neural network is appropriate for classifying patterns. Three layers make up the basic architecture: an input layer, a pattern layer, and an output layer.

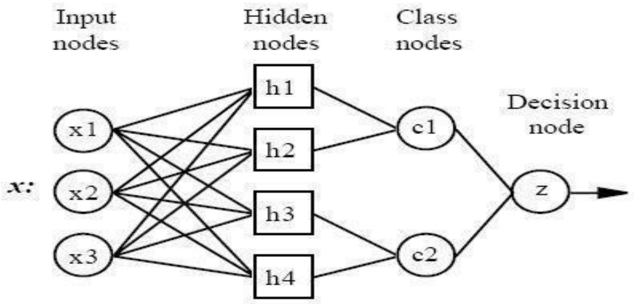


Figure: Architecture of a PNN

There are four layers in all PNN networks:

- Input layer — In the input layer, each predictor variable has its own neuron. N-1 neurons are utilised in the case of categorical variables, where N is the number of categories. By taking the median out and dividing by the interquartile range, the input neurons (or processing before the input layer) normalise the range of the data. The hidden layer's neurons in turn get the values from the input neurons.
- Hidden layer — Each example in the training data set contains a single neuron in this layer. Along with the target value, the neuron also stores the values of the case's predictor variables. When given the x vector of input values from the input layer, a hidden neuron calculates the test case's Euclidean distance from the neuron's centre point and then utilizes the sigma value to apply the RBF kernel function (s). The pattern layer's neurons receive the resulting value.
- Pattern layer / Summation layer — A neural implementation of a Bayes classifier, the pattern layer uses a Parzen estimator to approximate the class-dependent Probability Oensity Functions (POF)[6]. By minimising the estimated risk of erroneously classifying the training set, the Parzen estimator calculates the POF. As more training samples are used, the classification using the Parzen estimator approaches the actual underlying class density functions.

  Each input vector in the training set has a corresponding processing element in the pattern layer. In order to avoid some output classes being wrongly inclined and producing subpar classification results, each output class should have an equal amount of processing components. In the pattern layer, each processing component is trained once. When an input vector coincides with the training vector, an element is trained to return a maximum output value. When training the network, a smoothing factor is added to help with generalization. Only the input vector that matches another input vector the best wins and produces an output in the pattern layer, which classifies the input vectors based on competition. Thus, for each input vector, only one categorization category is produced. No output is produced if there is no connection between the input patterns and the patterns that are programmed into the pattern layer.

- Decision layer — For PNN networks, the decision layer is dissimilar. In PNN networks, the decision layer compares the weighted votes acquired in the pattern layer for each target category and selects the target category that has received the most votes.

Conceptually, probabilistic neural networks and K-Nearest Neighbor (k-NN) models are related. Probabilistic neural networks and K-Nearest Neighbor (k-NN) models have a conceptual connection. Consider this figure:

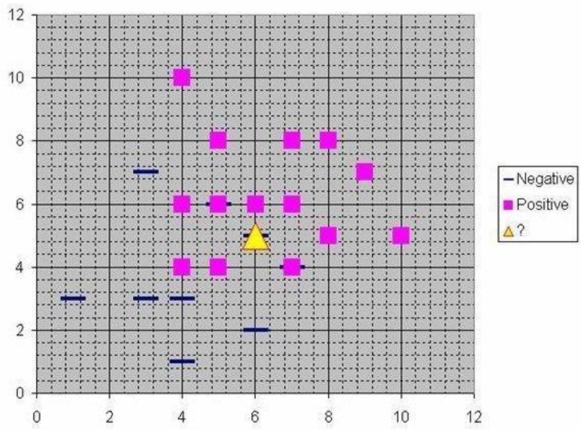


Figure: How PNN network work?

Assume that there are two predictor variables, x and y, for each example in the training set. According to the figure, the examples are plotted using their x,y coordinates. Assume that there are two categories for the target variable: positive, represented by a square, and negative, represented by a dash. Now imagine that we are attempting to forecast the outcome of a novel example, which is symbolised by the triangle with the predictor values x=6, y=5.1.

Keep in mind that the triangle is almost accurately positioned on top of a dash signifying a negative number. But compared to the other dashes, which are grouped below the squares and to the left of the center, that dash is in a somewhat unusual location. Thus, the underlying negative value can be an uncommon instance. Depending on how many nearby points are taken into account, this example's nearest neighbour classification is conducted. The new point should obviously be labelled as negative since it is on top of a known negative point if 1-NN is applied and only the closest point is taken into account. However, if the closest nine points are taken into account and the 9-NN classification is employed, the effect of the eight nearby good points may outweigh the nearby negative point.

Support vector machine:

The support vector machine, in its simplest form, is a binary learning machine with some incredibly elegant properties. It may be simplest to begin by discussing the case of separable patterns that arise in the context of pattern categorization in order to describe how the machine operates. The machine's central concept can be summed up as follows in this context: The support vector machine builds a hyperplane as the decision surface from a training sample in a way that maximises the margin of separation between positive and negative examples.

In order to cope with the more challenging scenario of nonlinearly separable patterns, this fundamental idea is expanded in a systematic manner. The inner-product kernel between a "support vector" xi and a vector x derived from the input data space is a key idea in the creation of the support vector learning algorithm. Most significantly, the learning algorithm used a small selection of data points from the training sample to create the support vectors. In fact, the learning algorithm used in the creation of a support vector machine is often known as a kernel technique due to this fundamental characteristic. The kernel method, which is essential to the creation of a support vector machine, is, however, optimal, with convex optimization serving as the basis for this superiority. The cost of achieving this highly desired feature of the machine is an increase in computational complexity.
The Support Vector Machine is a supervised learning method that primarily targets classification but can also be applied to regression. The algorithm searches for the best hyperplane that can be used to classify fresh data points based on the labelled data, and this is the significant idea (training data). In two dimensions, the hyperplane is a simple line A learning algorithm would often use representative features to reflect the most common traits (what sets one class apart from another) when categorising a class (so classification is based on dissimilarities between classes). The SVM functions in the opposite manner. It locates the most comparable class examples. Those will be the support vectors. The basic steps of the SVM are: choosing two hyperplanes (in 2D) that divide the data into equal segments without any points in between (red lines); maximising their distance (the margin); and choosing an average line (in this case, the line passing through the middle of the two red lines) as the decision boundary.

LIBSVM is integrated software for distribution estimation, regression, and support vector classification. In order to get over the limitation of linear support vector machines, it offers multiclass classification.

Intelligent decision support system:
A Decision Support System is often software created to assist decision-makers in solving practical decision problems utilising specialised data and models. The use of computational tools facilitates the resolution of difficult, ambiguous, and unstructured decision-making issues.

In order to help identify rules for the IDSS, an Intelligent Decision Support System makes considerable use of Artificial Intelligence techniques like Case-Based Reasoning, cluster analysis, and categorization. In the current informational trend, IDSSs are widely used. As a result of the widespread usage of the internet, several systems were created to aid users in navigating, the most prominent of which are recommender systems (a class of IDSS), which are present, for instance, on most e-commerce websites. In order to select the optimum machine learning algorithm for a given task, we must first solve an optimization problem in which we must identify the algorithm and hyper-parameters that will minimise a specified error function. However, it can also be viewed as a decision problem where the machine learning user (who has an issue that needs to be solved by machine learning) is the decision maker and must choose how to apply machine learning techniques most effectively to come up with a better solution for the problem.

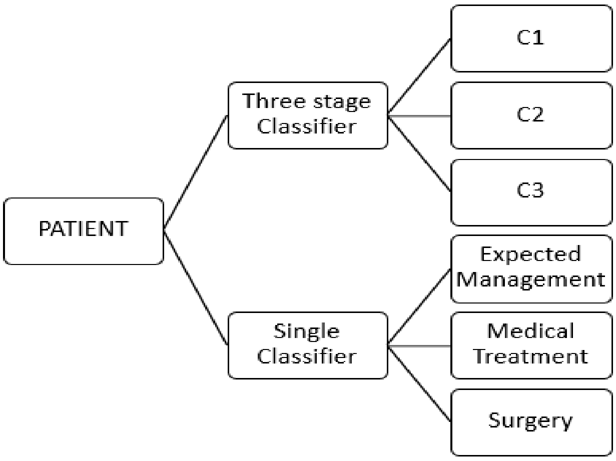


Fig: Three-stage classifier

Single Classifier (SC) was created for each of the three algorithms used in this investigation. However, there are enough instances where the patient's development or misclassification necessitates a change in the initial course of treatment. As shown in Fig.2, we have also created a three-stage classifier (3SC) by concatenating the three sub-classifiers C1, C2, and C3 in order to explain misclassification scenarios and increase the ratio of initial right classifications. In situations where surgery is not chosen as the initial course of treatment, this new classifier makes the claim that it will increase accuracy through reclassifications. Between individuals whose circumstances necessitate surgical intervention and those whose cases do not, the first classification (C1) is formed. Next, we divide patients who do not need surgery into those who must adhere to an expectant management protocol and those who should get pharmaceutical treatment (C2). However, as was already said, there are some situations where a patient who was first treated with medicine may end up needing surgery because the medication has not worked or because the initial diagnosis was incorrect. Avoiding this situation is a good idea. As a result, a third classifier (C3) is in charge of reanalyzing all instances that have been suggested for medication and reclassifying them as either requiring surgery or medication. Because of this, C3 corrects the classifications produced by C1 and C2.

The various design parameters for the algorithms SVM, MLP, and PNN are displayed in Table 1. Using the full converted dataset to train and test a particular algorithm is a more advanced method than utilizing a test and train dataset. Cross validation is a technique that might be used in a test harness to accomplish this. The dataset must first be separated into several equal-sized groups of cases (called folds). The model is then trained on all folds with the exception of one, and the tested model is applied to the omitted fold. Each fold is given a chance to be excluded and act as the test dataset by repeating the process. The performance metrics are then averaged over all folds to determine the algorithm's potential for solving the problem. We utilised a 20-fold cross validation and 90% input data for training and validation.

Table 1: Design parameters of MLP,PNN,SVM

MLP	Values
Number of iterations	**10**
Learning rate	**0.2**
Training cycles	**10**
Number of generations	**10**

Number of ensemble MLP	**4**
Threshold	**1**
Activation function	**Binary linear activation function**

Probabilistic Neural Network	Values
Input	
Number of iterations	
Smoothing factor	**6.1**

SVM	Values
Type	**C-SVC**
Kernel	**RBF**
Kernel option	**9**
Lambda	**1x10^-7**
Epsilon	**1.0E-3**

In this trial, MTX was administered systemically to 736 cases with unruptured tubal pregnancy. Retrospective evaluation and analysis were done on the sonographic characteristics of traditional transvaginal sonography, elastography, and serum hCG levels before and after MTX therapy. In order to find an ectopic sac in the high site, determine the size, location, and position of the uterus, and assess for free intraperitoneal fluid, a transabdominal or transvaginal pelvic scan is performed. For TVS, a transducer frequency between 5 and 10 MHz is often ideal. Our database had uneven classes, incorrect data entry, and missing data throughout the preprocessing stage.

The minority class duplicate examples are added at random to the training dataset to oversample it. Examples are chosen at random using substitutes from the practise dataset. This suggests that samples from the minority class can be chosen from the initial training dataset, added to the new, "more balanced," training dataset, and then returned or "replaced" in the initial dataset so they can be selected again. When there are numerous duplicate cases for a single class and the distribution is skewed, this strategy can be helpful for machine learning algorithms. This could entail learning coefficient-based methods repeatedly, such as artificial neural networks built on the basis of stochastic gradient descent. Beta-HCG, diagnosis date, last menstrual cycle, location, and attributes linked to surgery, pregnancy management, medical treatment, etc. are among the attributes considered in this study.

RESULT ANALYSIS:

The following parameters can be used to assess the classifier's performance: Sensitivity: It measures the percentage of true positives that are accurately recognized.

Sensitivity = TrP. / (TrP + FaN)

Where, TrP = True Positive: Abnormality correctly classified as Abnormal, FaN = False negative: Abnormality incorrectly classified as normal. Specificity: It measures the proportion of negatives which are correctly recognized.

Specificity = TrN./(FaP + TrN),
Where, FaP = False Positive: Normal incorrectly classified as Abnormal TrN = True negative: Normal correctly classified as normal.

Total accuracy: (TrP + TrN). / (TrP + TrN +FaP+ FaN)

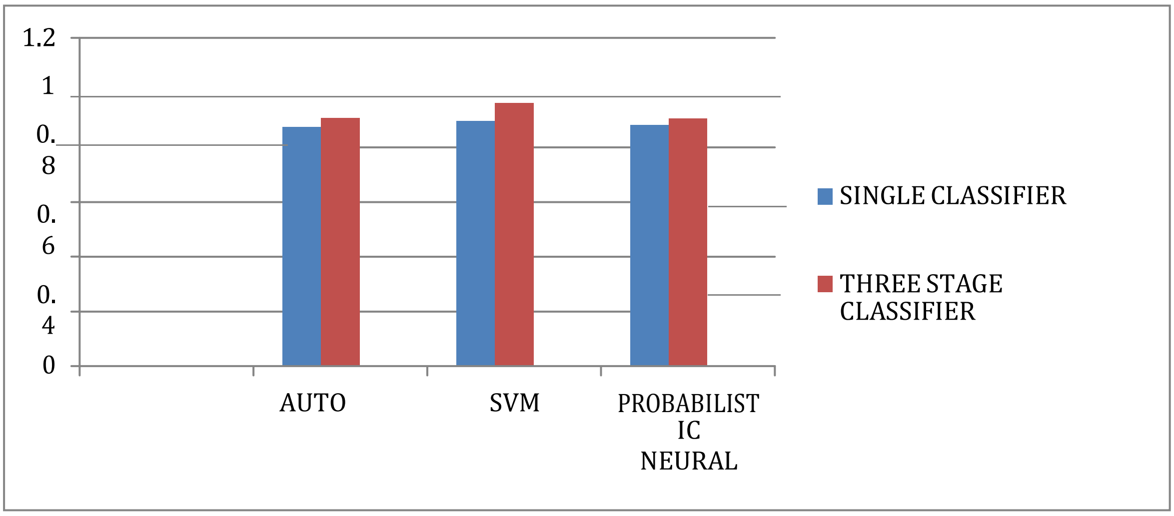
Table 2 shows that accuracy of the MLP, SVM, PNN algorithms.

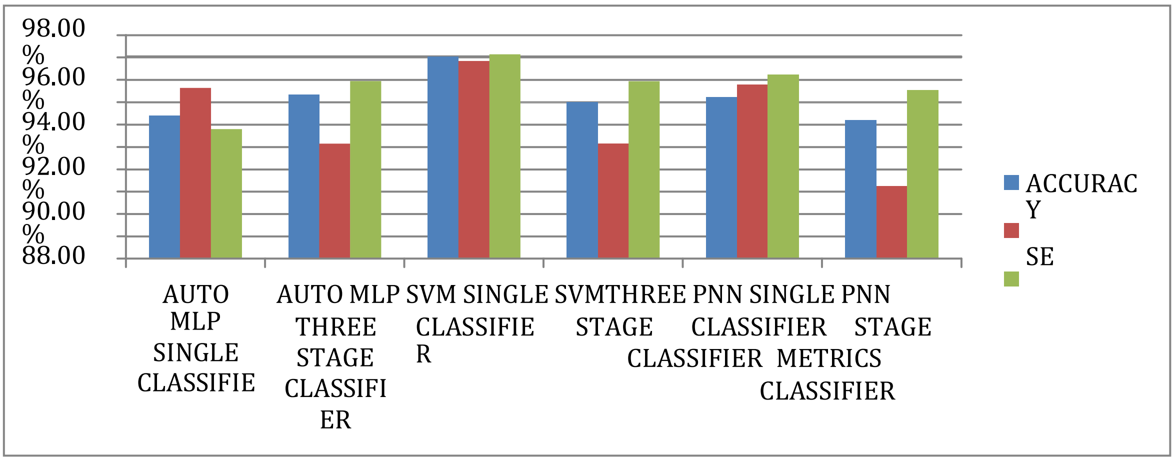
ALGORITHM	RP	SINGLE CLASSIFIER METRICS	THREE STAGE CLASSIFIER METRICS
		ACCURACY	ACCURACY
AUTO MLP SURGERY	240	87.4%	90.8%
MEDICAL TREATMENT	266		
EXPECTANT MANAGEMENT	266		
SVM SURGERY	240	89.7%	96.1%
MEDICAL TREATMENT	266		
EXPECTANT MANAGEMENT	266		
PROBABILISTIC NEURAL NETWORK SURGERY	240	88.2%	90.5%
MEDICAL TREATMENT	266		
EXPECTANT MANAGEMENT	266		

Table 3

	ACCURACY	SE	SPE
AUTO MLP SINGLE CLASSIFIER METRICS	90.8%	93.3%	89.6%
THREE STAGE CLASSIFIER METRICS	92.7%	88.3%	93.9%
SVM SINGLE CLASSIFIER METRICS	96.1%	95.7%	96.3%
THREE STAGE CLASSIFIER METRICS	92%	88.3%	93.9%
PROBABILISTIC NEURAL NETWORK SINGLE CLASSIFIER METRICS	92.50%	93.60%	94.50%
THREE STAGE CLASSIFIER METRICS	90.40%	84.50%	93.10%

Area Under Curve





CONCLUSION:

The MLP, SVM, and PNN algorithms show that the single classifier and three-stage classifier performed the best, with 89.7% and 96.1%, respectively. PNN also performed well in classification, but at a lower level than SVM. MLP was lower than the result obtained with SVM and PNN. In our database, the initial treatment was correctly assigned by the medical team in 87.6% of the cases. This accuracy is marginally below our single classifier's greatest performance (SVM, 89.7%). However, with two of the three-stage classifiers, especially the SVM algorithm is greatly improved. Finally, Table 3 shows two categories of classification (surgery, no surgery) for the algorithms implemented. For this type of classification, the SVM algorithm was also the one with the highest precision, improving both sensitivity and specificity. In general, the remaining algorithms enhanced sensitivity but decreased accuracy and specificity.

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