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PREDICTION OF THE FINANCIAL STRESS AND HEALTH RISK IN MATERNITY USING MACHINE LEARNING FOR LOW SOCIO-ECONOMIC AREAS OF LAHORE

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Abstract
Maternal mortality is the global cause that is affecting the health status of the worldwide population. In low-income countries like Pakistan, financial stress is very common and has been considered a vital cause of maternal mortality. In this research, we have conducted an exploratory study at BHU Kahna Kacha Lahore and general hospital Lahore to understand the financial, health care, and maternity issues in low-socio-economic areas. The sample size used in this study contained 104 expecting mothers, 10 husbands, 3 doctors,1 LHV, and 1 midwife. (The saturation is considered while defining sample size). After thematic analysis and data processing, we extracted the key features that affect maternal mortality. These features are age, Locality, Education Level, Pregnancies Number, Month of pregnancy, Checkups, Last Delivery Type, Income, Monthly Expense, Spent on Last Delivery, Private Tests Cost, Undiagnosed Disease Cost, Transport Cost. We used these key features after data preprocessing to train machine learning algorithms to predict the intensity of maternal health risk and their financial stress level. We trained Support Vector Machine SVM (with different kernels), K-Nearest Neighbors KNN, and Naïve Bayes NB models. We then validated it using cross-fold validation, and our validation measures were Accuracy and F1- Score. According to the results, Naïve Bayes is the best option for the prediction of health risk and financial stress levels. As this research work predicts HR and FS of expecting mothers, it can help the government, insurance companies, social work societies, and banks to devise new health policies, new pregnancy-related insurance schemes, and loan deals while viewing their causes.

INTRODUCTION

Maternal mortality is a global health problem because it affects both social and economic aspects of a family, a community, and a nation. About 295,000 women died globally due to complications from pregnancy in 2017 while the global maternal mortality rate was 211 D/M lives (Source: WHO). In

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low-income countries like Pakistan, MMR has a high magnitude that causes many deaths yearly. Many communication and health strategies are introduced that are helping women in all the world regions to minimize the effect of maternal mortality by fighting against its causes. [1] Causes of maternal mortality are of two types: Direct causes which are mostly related to medical like abortion, hypertension, hemorrhage, embolism, sepsis, etc., and occur during delivery time. While indirect causes are mostly social and economic factors. Indirect causes sometimes are a reason for direct causes so lives can be saved if direct causes are taken care of. Indirect causes include stress, poor prenatal care, financial stress, improper medication, distance to facilities, lack of information, cultural beliefs and practices, education level, low age marriages, social factors (low educated clinical staff). [2] Among all these causes, financial stress is most vital because if somehow financial stress is reduced, people will be able to afford good facilities, medication, diet, which can reduce the impact of these causes on maternal health. Our proposed research work focuses on identifying factors that affect the health risk and financial stress in low socio-economic areas of Pakistan, which later helps to identify the financial stress and health risk of a new patient using machine learning algorithms. This research can help the government, insurance companies, social work societies, and banks to devise new health policies, new pregnancy-related insurance schemes, and loan deals. This would ensure the in-time health facilities reduce the risk of either maternal health or newborn child health.

Methodology

Our proposed study consists of two parts 1) The exploratory study was conducted to collect data from the targeted population, and then analyzed using thematic analysis from which patterns were identified that affect the health risk and financial stress. 2)Machine learning Part are used to predict maternal health risk and their financial stress. Figure 1 shows the phases of our proposed methodology.

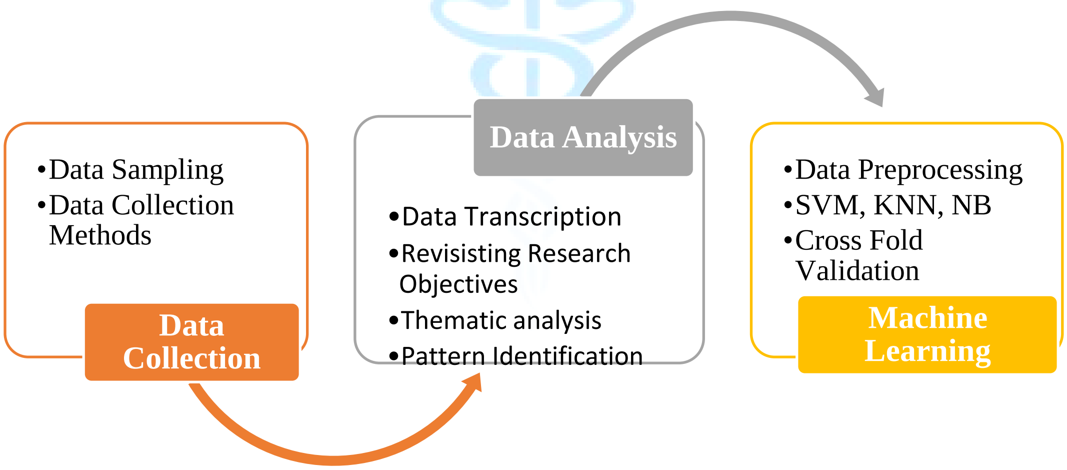

Figure 1: Methodology Layout

Data collection

We conducted an exploratory study to understand the situation of maternal healthcare and financial conditions in maternity in low socio-economic areas of Lahore. Our data collection process consists of data sampling and data collection methods.

Sampling

If in an exploratory study the target population is huge, the Sampling technique is used to select a group of people that fulfill the requirement of research interest.

Target population: In this study, the targeted population was i) the first group of experts who were working in the domain of maternal and reproductive health system, lady health workers from the targeted area that knows better about the maternity issues of that area. ii) second groups contain expecting mothers, women of reproductive age, and their husbands that are available at the health centers

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from the rural and urban areas. The target population belonged to the rural and peri-urban area of Lahore that is BHU Kahna Kacha, and General hospital Lahore.

Sampling techniques: For sampling the population, we used two sampling techniques i) snowball sampling, Our main participants were expecting mothers and medical experts. When we started our fieldwork, doctors refer different participants for interviews. Similarly, the participants also talk about the other participants. ii)Convenience sampling, sampling was done according to the participant's availability and easiness at the Basic Health center and General hospital of Lahore.

Sample Size: The sample size used in this study contained 104 expecting mothers, 10 husbands, 3 doctors,1 LHV, and 1 midwife. (The saturation is considered while defining sample size).

Data Collection methods

In this study, the data collection techniques were in-depth interviews, questionnaires while the data collection tools were voice recording and notes. An open-ended questionnaire was used which included the consent and questions about health risks, financial conditions, and basic information. Structured and semi-structured interviews were conducted for this research at the BHU Kahna Kacha Lahore and general hospital Lahore. First 60 expecting mothers and 2 doctors, interviews were conducted face to face using open-ended questions, and the duration was 40 to 50 minutes. While the rest of the interviews were conducted online using close-ended questions, and the duration was 30 to 40 minutes. All the ethical rules considered while conducting an interview These interviews were conducted in both Urdu and English languages using voice recordings and notes. (Voice recording include the consent of participants)

Data Analysis

To organize our data to extract meaningful information from it, we used the process shown in Figure 2.

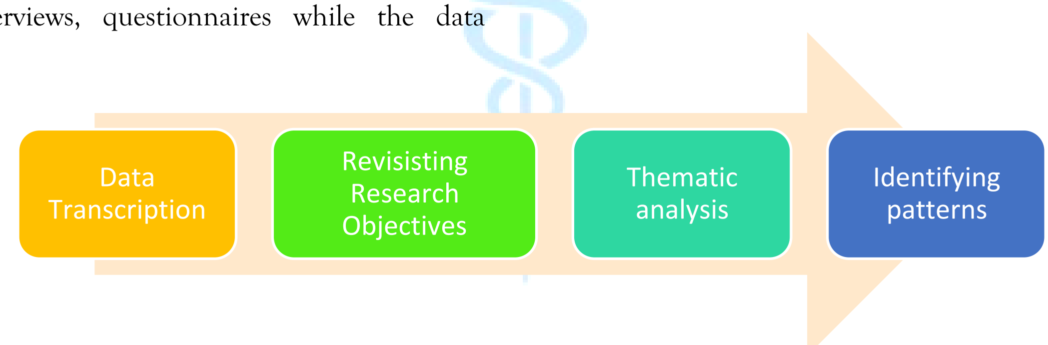

Figure 2: Data Analysis Stages

Data Transcriptions: The recorded interviews and notes were converted to written forms called transcriptions to avoid errors and incorrectness. The transcription is written in the same language in which interviews were conducted.

Revisiting research objective: After completing the transcription process, the research objectives are reconsidered before analysis. The main research objective of this study is to find out the maternal health issues and the consequences of financial stress on maternal health and factors leading towards maternal mortality.

Thematic analysis: Thematic analysis is used to figure out the information gather from participants. In this study, the NVivo software is used to done automatic thematic analysis. The extracted themes were age, Locality, Education Level, Pregnancies Number, Month of pregnancy, Checkups, Last Delivery Type, Income, Monthly Expense, Spent on Last Delivery, Private Tests Cost, Undiagnosed Disease Cost, Transport Cost, Decision power.

Data Refinement & Pattern Identification: In data refinement, we refined the themes using literature work and experts' interviews that directly affect

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maternal health and financial stress. The refined features are Checkups, Ultrasound, HB, BP monitoring, hepatitis, Blood Sugar Level, Anemia, diabetes, Emergency Cesarian, hepatitis, High blood pressure, Total Expense on Delivery, Borrow money for medication.

These features are then used to annotate the records by the voting technique that labels the intensity level of HR and FS (low medium high) of each record. For labeling, we divided numerical features into three ranges and assigned HR and FS intensity levels to them. Similarly, for each note of the categorial feature, we assigned an intensity level. Each value of the feature votes against intensity levels (low, medium-high) of each record. We label each record with the highest voted intensity level of HR and FS. After plotting each feature against HR and FS we observed the following patterns.

A. Trends of missing checkups

After analyzing the collected data, we identified the following two trends,

- Women frequently having checkups
- Women having non-regular checkups

These two trends are mostly found with the classification of age and number of pregnancies. Figure 3,4, 5 & 6 shows the impact of age and no of pregnancies on health risk and financial stress. Women having first or second pregnancies are more responsive about checkups, tests, and medications. They are mostly young age girls who are newly married and have no financial stress about their households, so the health risk is also lower in that category. On the other hand, women having 3rd, 4th, or 5th pregnancies are not as responsive about their health-related checkups. They do not go for regular checkups, even do not take care of checkups and medication due to financial reasons.

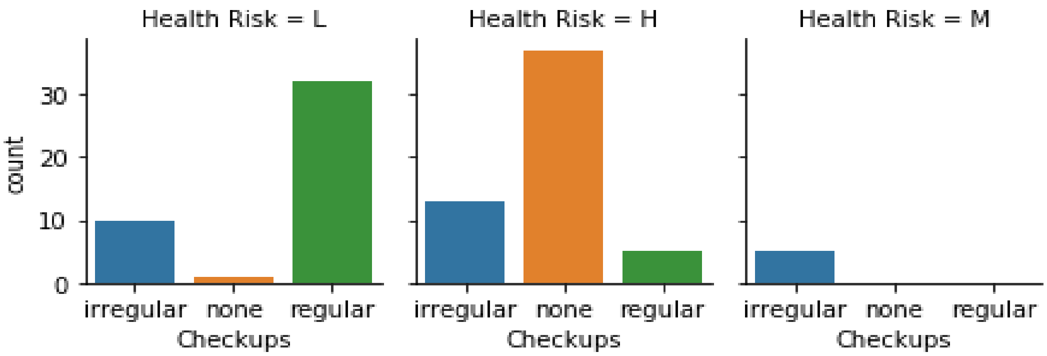

Figure 3: Impact of missing checkups on HR.

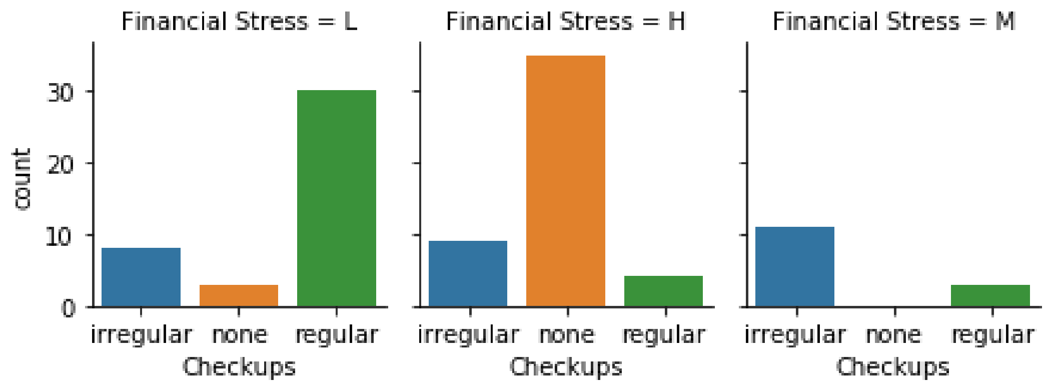

Figure 4: Impact of missing checkups on FS.

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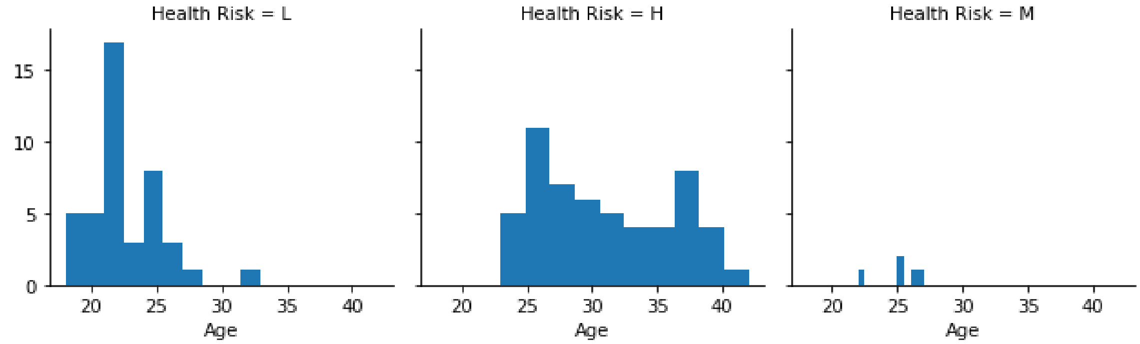

Figure 5: Impact of age on HR.

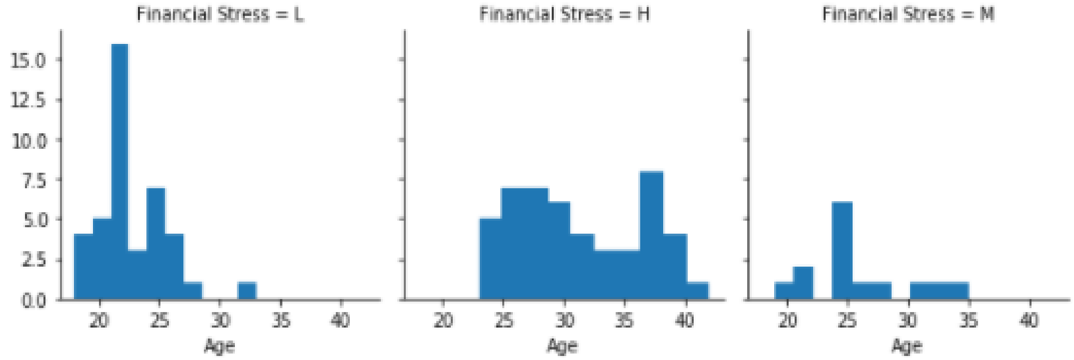

Figure 6: Impact of age on FS.

These two classified members' reviews are explained with feedback by women while conducting in-person interviews.

Women said

"It's my first pregnancy, and I am very happy. My family is very cooperative. They are also very happy. I have done with all my tests and follow my checkups regularly. It's my 8th month of pregnancy, and very hopeful for normal delivery. Our monthly income is not too much, but my husband manages my medical expenses".

Other women said

"It's my third pregnancy, and I have two daughters. I belong to a very conservative family. They want my next baby should be a son. It's my seventh month of pregnancy. I am here for an ultrasound; my mother-in-law convince a doctor to tell her about the gender of the baby. I have done with my basic test but did not follow my checkups".

Other women said:

"My name is Shabana, and I am from kahna kacha. It's my 7th month of pregnancy. I have four daughters and one son. The two elder sisters go to a nearby govt school. My husband is a laborer. I worked as a maid and earned 3000 a month. I did not follow my medication or test because I know everything about it now, as I have five kids already. My last delivery was cesarian. If I follow my medications and test, I can't manage my budget. Today I am here because of my BP shots last night, and I have pain in my lower belly. The doctor suggested an ultrasound".

Other Women said

"My name is Rakshana. My age is 32, and it's my 9th month of pregnancy. I had three daughters. I did not follow my medication and have no checkups yet. It's

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my nine-month, and I did not feel any movement of the baby, and ten-month is started. I was expecting normal delivery at home. My mother-in-law did not allow me to visit the hospital as I already have a big family and can't afford medication cost".
(After getting a checkup from the doctor, she faced an urgent operation and gave birth to a dead baby girl.

B. Lack of knowledge

Education is an important aspect of our research. Women having knowledge about the basic realities of pregnancy, the importance of medications do only consider these realities and go for their solution. On the other hand, women with a lack of knowledge do not consider medication and believe in some myths and non-existing religious terms. Figure 7 & 8 shows that women with a lack of knowledge get caught in complexities during the pregnancy time period. As a result, they face high health risks. Then financial stress will also be higher in this community.

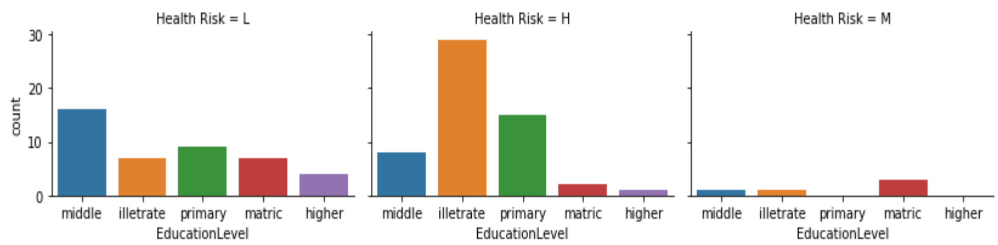

Figure 7: Impact of Education Level on HR.

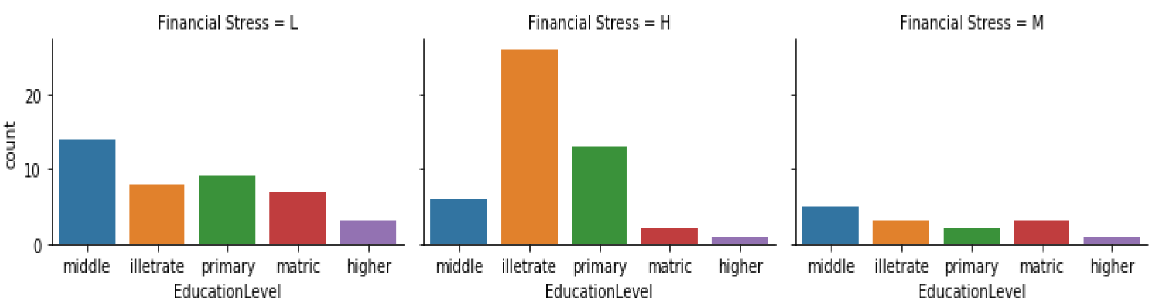

Figure 8: Impact of Education Level on FS.

Women said

"My name is Ayesha, and I am 26 years old. I have a daughter and a son, and now it's the 7th month of pregnancy. I don't know how to read and write. My mother-in-law is the decision-maker of my family. I did my ultrasound in the last checkup, and the doctor tells me that my HB is very low. If I didn't do proper medication, then I will face premature delivery or a weak baby delivery that may lead to neonatal death. I don't know about the procedures of checkups. In my last two deliveries, my mother-in-law doesn't allow me to go to the hospital. They think normal deliveries can be done at home. My mother-in-law just allows me once for a checkup".

Women said

"I am in the last month of pregnancy, and my mother-in-law give me Castrol oil and said your delivery would be normal after its use. I drink that oil, but after some time, I have severe pain, and my family took me to BHU in an emergency, but they refer me to the hospital. The doctors do the operation, but I lose my child".

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C. Distance from the health center

Distance health facilities still remain an obstacle to proper health treatment during pregnancy. Accessibility of health facilities is also an important issue in areas where women couldn't find health centers near about. Figure 9 & 10 shows that it is less likely that a woman will receive proper maternal treatment where the distance from the closest health center is long.

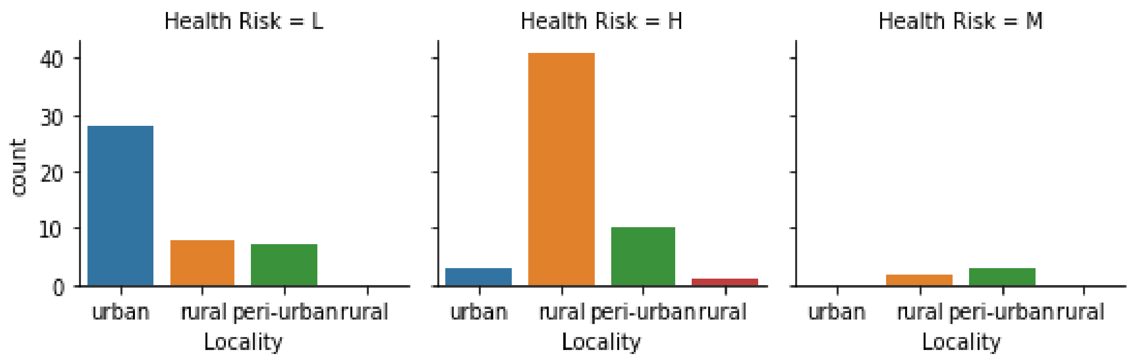

Figure 9: Impact of Locality on HR

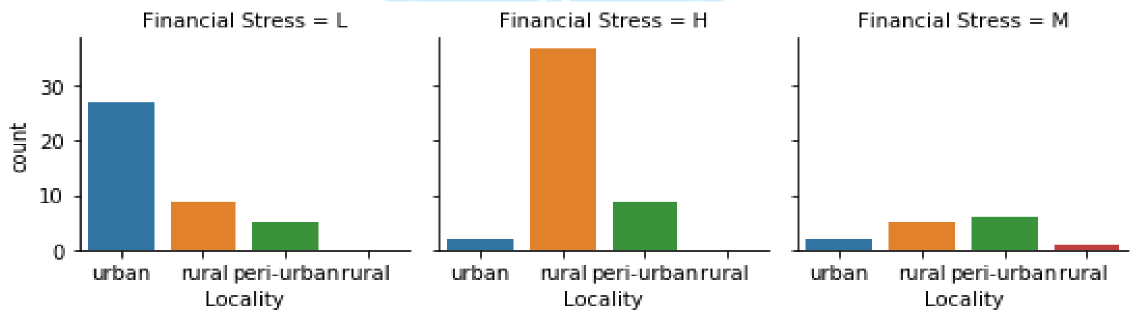

Figure 10: Impact of Locality on FS

D. The consequence of Undiagnosed diseases

Missing medical checkups, tests, and medication results in undiagnosed diseases. It also increases the risk of problems where healthcare providers get into difficult positions to manage the condition, and things get to a serious stage and result in high cost. These complications affect not only the mother's health but also the baby's health. Some of the diseases are as follow,

i. Diabetes:

Diabetes is one of the undiagnosed diseases that can negatively affect the health of women and babies. The resultant disease affects the baby organs as their shapes change. There are chances that the baby gets abnormal. One of the biggest risks of this disease is that babies grow much larger than normal. This results in operation, which not only increases the overall expense but also is more dangerous for the mother's health. The figure shows the impact of undiagnosed disease on HR and FS.

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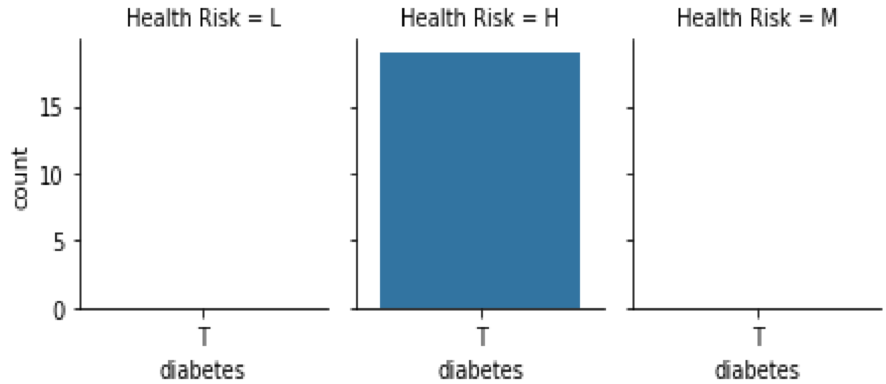

Figure 11: Impact of undiagnosed diabetes on HR.

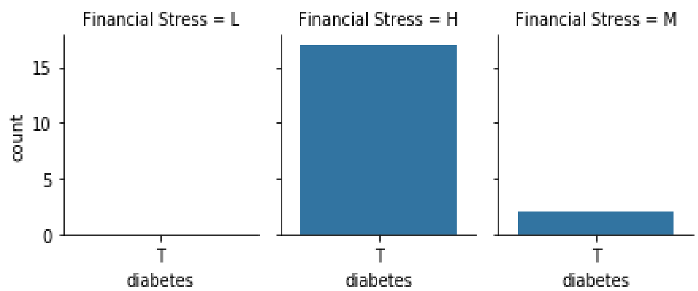

Figure 12: Impact of undiagnosed diabetes on FS

Women said
"My name is Bushra. I am 36 years old. I have six children, and it's my 8th month of pregnancy. I worked as a maid and earned 3000 a month. I am a diabetic patient. I lose my last child due to this disease. I didn't know that I was a diabetic patient in my last delivery. It was premature delivery because my BP and diabetes level increases at a very high level. The baby was very weak, so he couldn't survive. Now I follow my checkups and follow medication".

Another woman said
"I don't know. I was a diabetic patient, and I have five children. But in my previous pregnancy, I face an emergency cesarean due to which my baby is abnormal. But I know about these medications, expenses that are endless when it comes to the hospital, and I already have five children, so I know what to do and what will happen. I don't need any medication".

ii.Hepatitis:
Hepatitis is a very dangerous disease if not diagnosed on time. It can threaten the life of the mother as well as babies if they get to a serious stage during pregnancy. It sometimes affects very silently as it shows no signs sometimes. It can be severe in babies, and newborn babies are at high risk of becoming carriers. If hepatitis gets to severity, it results in dead baby delivery and can also affect the organs of the mother. All this becomes more difficult to handle at serious stages and also becomes more expensive.

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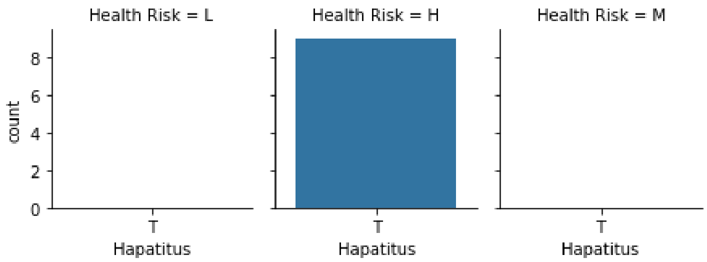

Figure 13: Impact of undiagnosed hepatitis on HR.

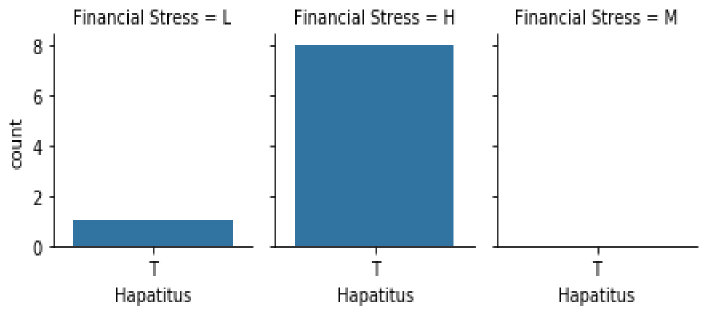

Figure 14: Impact of undiagnosed hepatitis on FS.

iii. High Blood Pressure

High blood pressure poses various risks not only on a mother's health but also on babies' health. It can sometimes cause severe health complications for both mother and the developing baby. When it is not monitored and treated, it can lead to mortality which is a serious issue for mother and baby. High blood pressure can result in a low-weight baby as the baby's ability to acquire adequate oxygen and nutrients to thrive is hampered by high blood pressure.

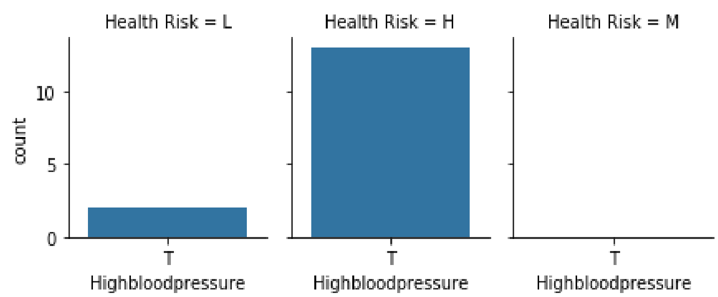

Figure 15: Impact of undiagnosed HBP on HR.

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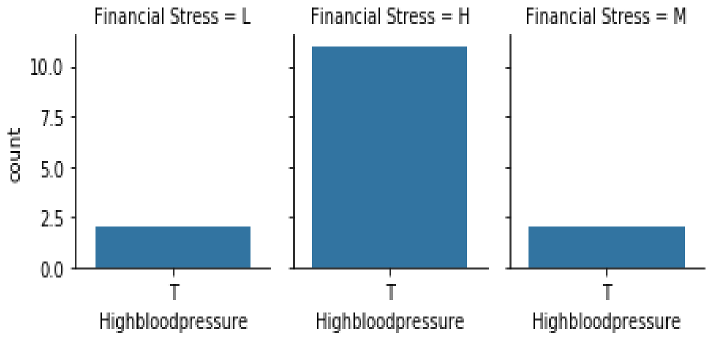

Figure 16: Impact of undiagnosed HBP on FS.

Women said:

"My name is Bushra. I am 36 years old. I have six children, and it's my 8th month of pregnancy. I worked as a maid and earned 3000 a month. I am a diabetic patient. I lose my last child due to this disease. I didn't know that I was a diabetic patient in my last delivery. It was premature delivery because my BP and diabetes level increases at a very high level. The baby was very weak, so he couldn't survive. Now I follow my checkups and follow medication".

Other women said:

"My name is Parveen. I am 38 years old. I have eight children. It's my 6th month of pregnancy. My husband works in a factory as labor and earns 20,000 per month. I did an ultrasound, and now it's my second checkup. I am a BP patient. My BP mostly remains higher than borderline. That's why I come for checkups occasionally, but the issue is I couldn't afford the cost of the medications. My sister-in-law died last year because she had BP issues and didn't come to checkups, she takes it normally, but in the 9th month of pregnancy, she had a swear attack of high blood pressure. The doctors did operate, but they couldn't save her. In case of emergency, the cost will increase, they arrange all of the money, but all get wasted. Now I am afraid of that case and come for a checkup".

E. Out of pocket expenses

The comparison of expenses at two different stages is shown below in the table. It clearly states that if you go for treatment on time, it not only reduces various health issues but also reduces the overall expenses of your treatment. By getting things done on time always prevent mother and newborn baby from having any unseen complications and reduce the chances of disease mentioned above. Table 1 shows some out-of-pocket expenses.

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Table 1: Out of pocket expenses

Expenses	Normal	In case of emergency
Transportation cost	Affordable rikshaw etc.	Ambulance
Private test cost	Not all test necessary	All test is done urgently
Indirect cost	Affordable	High cost

Machine Learning

In order to determine health risk and financial stress intensity levels for new cases, we processed the data further and used machine learning approaches on it. We trained the following models on 70% of our data and then used the remaining 30% of data to validate it. We have implemented these algorithms in python on the jupytor notebook version.

Data Preprocessing

For the implementation of classification models/algorithms, we processed the refined data from Data Refinement & Pattern Identification to the form it could be processed by models. We converted the categorial features like locality, checkups, education level, etc., to discrete numbers. We also discretized the continuous features like age, no. of pregnancies, Income, expenses, borrow money, etc., to discrete ranges. Then this data was fed to machine learning models for training, testing, and validation.

Support Vector Machine Algorithm

Support vector machine (SVM) is a supervised machine learning algorithm that is mostly used for classification as well as regression problems. SVM supports multi-class classification as well as effective in cases where the number of dimensions/ features are greater than the number of samples. For small datasets and provides good accuracy in prediction. It uses a subset of training points in the decision function (called support vectors), so it is also memory efficient. Due to these advantages, we selected SVM and used SKLearn.SVM.SVC library to implement three different models of SVM with different kernels (linear, rbf, sigmoid). Results of these models are discussed in the results chapter.

K-Nearest Neighbor (KNN) Algorithm

K- Nearest Neighbor is a supervised machine learning algorithm that can solve both classification and regressions problems but is mostly used in classification problems. To label a new point, KNN looks at the labels of k nearest points (nearest neighbors) and assigns a label to the new point, which most of the neighbors have. KNN is simple and easy to implement an algorithm. It fairs across all parameters of considerations and supports multi-class classification. It is also easy to interpret and has a low calculation time. Due to these advantages, we selected KNN and used **sklearn.neighbors. KNeighborsClassifier** to implement 3 NN. Model for our data. Results are shared in the results chapter.

Naïve Bayes Algorithm

Naïve Bayes algorithm is another supervised machine learning algorithm that is based on Bayes theorem with assumptions/features are independent. Bayes theorem provides a way of calculating posterior probability P(c|x) from P(c), P(x), and P(x|c) using the following equation

$$P(x) = \frac{P(c)P(c)}{P(x)}$$

❖ P(c|x) is the posterior probability of class (c, target) given predictor (x, attributes).
❖ P(c) is the prior probability of class.
❖ P(x|c) is the likelihood which is the probability of predictor given class.
❖ P(x) is the prior probability of predictor.

Naïve Bayes is simple and easy to build. It is useful even for very large datasets. It supports multi-class classification and outperforms even highly sophisticated classification algorithms. Due to these advantages, we selected NB and used sklearn.naive_bayes module to implement GaussianNB as it outperformed other NB. . Results are shared in the results chapter.

Cross fold validation

For the validation of the above algorithms, we used the cross-fold validation technique. In K Fold cross-

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validation, the data is divided into k subsets. One of the k subsets is used as the test set/ validation set, while the other k-1 subsets are put together to form a training set. This process is repeated k times. The error estimation is averaged over all k trials to get the total effectiveness of the algorithm/model. In this way, bias and variance reduce which makes this method effective.

Results and Discussion

For the prediction of health risk and financial stress intensities levels of people, we trained our selected machine learning models over 70% of our survey data while the other 30% was used for evaluation. To save machine learning algorithms from biasedness, we used cross-fold validation.

From the survey, we extracted 17 features that are shown in Table 2. Among these features, Financial Stress and Health risk are our target features, while others are key features to determine the intensity levels of health risk and financial stress.

Table 2: Key features affecting HR & FS

Sr. no	Features	Values
Personal Features		
1	Age	18-40 years
2	Locality	rural, peri-urban, urban
3	Education level	primary, middle, matric, intermediate, bachelors
Medical History		
4	Pregnancies Number	0 – 15
5	Month of pregnancy	1-9 months
6	Checkups	none, irregular, regular
7	Anemia	true, false
8	Diabetes	true, false
9	Emergency Cesarian	true, false
10	Hepatitis	true, false
11	High blood pressure	true, false
12	Last delivery type	none, normal, cesarian
Financial Status		
13	Savings	numerical
14	Total Expense on Delivery	numerical
15	Borrow money for medication	numerical
Target Features		
16	Financial Stress	low, medium, high
17	Health Risk	low, medium, high

According to the literature review and data analysis, the Health risk is dependent upon personal and medical features, while financial stress depends upon all three types of features mentioned in the table below. We have trained machine learning algorithms on these features and predicted our target features (Health Risk and Financial Stress). The performance of these algorithms is discussed below in the form of Accuracy and F1 Score.

Prediction Accuracy of Models

We have used five predictive models that are Naïve Bayes (NB), K – Nearest Neighbor (KNN), and Support vector machine (3 models with different Kernels), as our predictive models. We have evaluated their performance using 5-fold cross-validation. Mathematically, the proposed predictive models can be formulated as follows:

P_p represents predictive model where and p is the number of predictive models

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P_1 : K – Nearest Neighbor (KNN)
P_2 : Support Vector Machine (Kernel: Polynomial deg:3)
P_3 : Support Vector Machine (Kernel: Sigmoid)
P_4 : Support Vector Machine (Kernel: RBF)
P_5 : Naïve bayes (NB),

Accuracy of these predictive models P_p is calculated using Equation 1 where Acc_i denotes the accuracy of the predictive models P_i .

$$Acc_i = \frac{(TP_i + TN_i)}{(TP_i + FN_i + FP_i + TN_i)}$$

Equation 1: Accuracy formula for Predictive Models

The average accuracy of these predictive models P_i for 5 folds is calculated using Equation 2.

$$AVG(ACC) = \frac{\sum_{i=i}^{5} Acc_i}{5}$$

Equation 2: Average Accuracy for 5 readings

The accuracy of all the predictive models for each fold is present in Table 3. It also shows the average accuracy for Health risk and financial stress predictions.

Table 3 : Accuracy of Predictive models

P_p	Accuracy of FS.						Accuracy of HR.					
	F1	**F2**	**F3**	**F4**	**F5**	**AVG**	**F1**	**F2**	**F3**	**F4**	**F5**	**AVG**
P_1	0.71	0.43	0.57	0.60	0.50	0.56	0.86	0.95	0.81	0.85	0.95	0.88
P_2	0.48	0.43	0.43	0.7	0.60	0.53	0.81	0.81	0.81	0.90	0.95	0.86
P_3	0.52	0.61	0.52	0.4	0.4	0.49	0.33	0.33	0.33	0.35	0.25	0.32
P_4	0.48	0.48	0.38	0.4	0.5	0.45	0.67	0.71	0.67	0.65	0.65	0.67
P_5	0.76	0.76	0.76	0.75	0.75	0.76	0.62	0.95	0.95	0.95	0.80	0.85

If we plot the average accuracy values, we will get the following Figure 17.

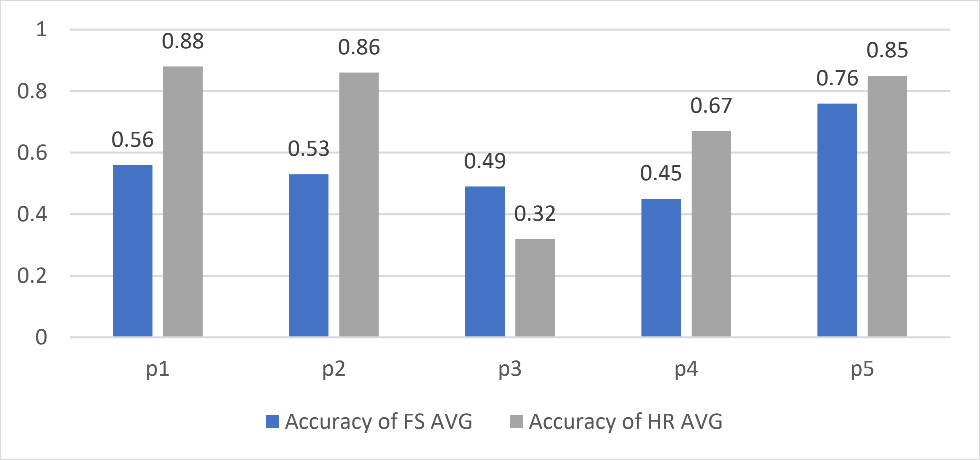

Figure 17: Average Accuracy Of Models

The graph shows that Naïve Bayes gives the best accuracy for FS and HR. So, Naïve Bayes is a good choice for the prediction of health risk and financial stress levels. For further confirmation, we have computed f1 score below.

Prediction F1-Score of Models

F1- Score of these predictive models P_i is calculated using Equation 3 where F1- Score i denotes the accuracy of the predictive models P_i

$$F1 - Score_i = \frac{(2 * Percision_i + Recall_i)}{(Precision_i + Recall_i)}$$

Equation 3: F1-Score formula for Predictive Models

Average $F1 - Score$ of these predictive models P_i for 5 folds is calculated using Equation 4.

$$AVG(F1 - Score) = \frac{\sum_{i=i}^{5} F1 - Score_i}{5}$$

Equation 4: Average F1 Score formula for 5 readings

The $F1 - Score$ of all the predictive models for each fold is present in Table 4. It also shows the

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average F1 - Score for Health risk and financial stress predictions.

Table 4: F1- Score of Predictive models

P_p	F1 Score of FS						F1-Score of HR.					
	F1	F2	F3	F4	F5	AVG	F1	F2	F3	F4	F5	AVG
P_1	0.66	0.41	0.57	0.58	0.49	0.54	0.83	0.93	0.77	0.85	0.95	0.87
P_2	0.43	0.35	0.32	0.67	0.57	0.47	0.79	0.79	0.77	0.88	0.95	0.84
P_3	0.46	0.57	0.50	0.28	0.26	0.41	0.26	0.29	0.30	0.26	0.20	0.26
P_4	0.35	0.31	0.21	0.28	0.38	0.31	0.61	0.66	0.61	0.60	0.60	0.62
P_5	0.76	0.78	0.80	0.76	0.75	0.77	0.65	0.93	0.95	0.95	0.87	0.87

If we plot the average F1 Score values, we will get the following Figure 18.

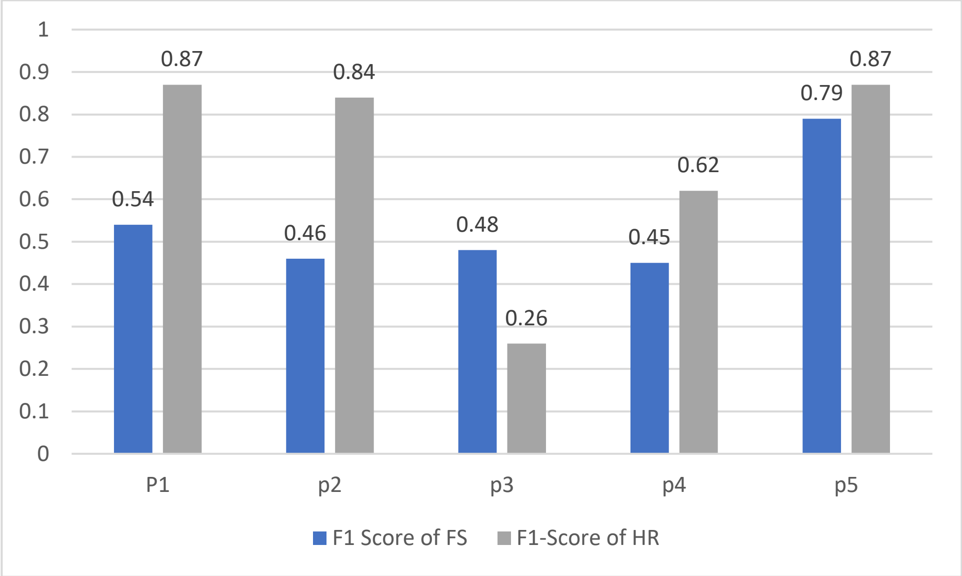

Figure 18: Average F1-Score of Models

This graph also shows that Naïve Bayes gives the best F1 Score for both FS and H.R. Hence, Naïve Bayes is a good choice for the prediction of health risk and financial stress levels.

Conclusion

In this research, we have conducted an exploratory study at BHU Kahna Kacha Lahore and general hospital Lahore to understand the financial, health care, and maternity issues in low-socio-economic areas. After thematic analysis and data processing, we extracted the key features that affect maternal mortality. These features are age, Locality, Education Level, Pregnancies Number, Month of pregnancy, Checkups, Last Delivery Type, Income, Monthly Expense, Spent on Last Delivery, Private Tests Cost, Undiagnosed Disease Cost, Transport Cost. Their relationship with maternal health risk and financial stress gave us different trends. Frequent checkups, regular tests, and proper medication trends were found in the young women who are experiencing either first or second pregnancy while expecting mother that already have 2 or more kids don't consider medication that important due to financial stress, which makes them highly prone to swear health risk. Women with a lack of knowledge believe in myths and non-existing religious terms. Far away health facilities also affect the maternal. Undiagnosed diseases at a delivery time increase the health risk and suddenly increase the cost, putting the whole family under financial stress and endangers the baby's health. Getting timely treatment not only keeps mother and child safe but also reduces out-of-pocket expenses.

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We used these key features after data preprocessing to train machine learning algorithms to predict the intensity of maternal health risk and their financial stress level. We trained Support Vector Machine SVM (with different kernels), K-Nearest Neighbors KNN, and Naïve Bayes NB models. We then validated it using cross-fold validation, and our validation measures were Accuracy and F1- Score. According to the results, Naïve Bayes outperformed all other models with an average accuracy of 0.76 for the prediction of health risk, and 0.85 is the average accuracy of financial stress intensity level. While the average F1-Score of Naïve Bayes for Health Risk prediction is 0.77, and 0.87 is the average F1-Score for the prediction of Financial Stress level.

According to the results, Naïve Bayes is the best option for the prediction of health risk and financial stress levels. As this research work predicts HR and FS of expecting mothers, it can help the government, insurance companies, social work societies, and banks to devise new health policies, new pregnancy-related insurance schemes, and loan deals while viewing their causes. This would ensure the in-time health facilities reduce the risk of either maternal health or newborn child health.

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