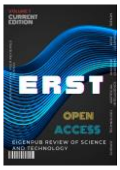

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Investigating Healthcare Centers' Willingness to Adopt Electronic Health Records: A Machine Learning Perspective

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ABSTRACT

Electronic Health Records (EHRs) are a vital component of modern healthcare systems, providing a comprehensive view of patients' medical histories and improving care coordination and patient outcomes. However, despite the potential benefits, the adoption of EHRs in healthcare centers remains a complex and challenging process. Understanding the factors that influence healthcare centers' willingness to adopt EHRs is crucial for developing effective strategies to overcome barriers to adoption and realizing the full potential of EHRs. Therefore, this study aimed to investigate the willingness of healthcare centers to adopt EHRs using advanced machine learning techniques. A sample of 150 IT personnel from different healthcare centers participated in the study. The study utilized Ensemble Voting Classifier and Stacking Classifier as classification algorithms to classify the willingness of healthcare centers to adopt EHR into three classes: i) unwilling to adopt EHR, ii) undecided, and iii) willing to adopt EHR. The results indicated that the Ensemble Voting Classifier with additional features showed the best performance among all models, achieving an accuracy of 0.82. Naive Bayes with additional features and the Ensemble Voting Classifier without additional features followed with accuracies of 0.79 and 0.69, respectively. Furthermore, the study found that healthcare centers with technical expertise were more willing to adopt EHR, while cost barriers caused unwillingness to adopt EHR. Healthcare centers with supportive infrastructure were also found to be more willing to adopt EHR. Finally, the fear of workflow disruption was identified as a cause of unwillingness to adopt EHR. This research contributes to a better understanding of the factors that influence healthcare centers' willingness to adopt EHR. These findings may inform strategies to overcome barriers to EHR adoption and improve the quality and efficiency of healthcare services.

Keywords: *Adoption, Electronic Health Records (EHRs), Ensemble Voting Classifier, Healthcare centers, Stacking Classifier*

I. INTRODUCTION

Electronic Health Records (EHRs) are transforming the healthcare industry, streamlining patient care, and improving outcomes. EHRs are digital records of patients' health information that can be accessed and shared by authorized medical personnel. They are replacing paper-based records, which were often difficult to access and share, and prone to errors and loss. With EHRs, medical personnel can access patient information from anywhere, at any time, with a few clicks of a button.

EHRs contain comprehensive information about patients' medical history, including diagnoses, allergies, medications, test results, and treatment plans. This information is stored in a secure and encrypted format, making it difficult for unauthorized individuals to access. EHRs also provide real-time access to patient data, which can help healthcare providers make more informed decisions about patient care.

EHRs can reduce the risk of medical errors, such as prescribing the wrong medication or administering the wrong dose. EHRs also provide alerts for potential drug interactions, allergies, and other potential issues, helping healthcare providers make more informed decisions about patient care. EHRs can reduce administrative burden and paperwork, allowing healthcare providers to spend more time with patients. EHRs also make it easier to track patient billing and insurance information, which can help healthcare providers manage their finances more efficiently.

EHRs also improve the efficiency of healthcare delivery. With EHRs, healthcare providers can access patient information quickly and easily, without having to search through paper-based records. This saves time and improves the quality of care that patients receive. EHRs also make it easier to share patient information between different healthcare providers, such as primary care physicians, specialists, and hospitals. EHRs also have the potential to improve healthcare outcomes. With access to comprehensive patient information, healthcare providers can make more informed decisions about patient care. This can lead to better outcomes, such as improved management of chronic diseases, reduced hospital readmissions, and fewer complications. With access to large amounts of patient data, healthcare providers can identify trends and patterns in the health of specific populations. This can help healthcare providers develop targeted interventions and preventive measures.

One of the significant barriers to EHR implementation is the high cost associated with hardware, software, and training. The cost of EHR implementation can be prohibitive for small healthcare organizations or those with limited budgets. The financial burden of implementing and maintaining EHRs can strain the resources of healthcare providers. The high cost of EHRs can also create a digital divide, with larger healthcare providers with more substantial budgets being able to afford better EHR systems than smaller providers.

Another challenge of EHR implementation is the cost of maintenance and upkeep. Like all software systems, EHRs require continuous maintenance and upgrades to ensure optimal performance. Healthcare providers must invest significant resources to ensure that their EHR system is up-to-date and functioning correctly. The costs of maintenance and upkeep are ongoing and can add up over time. Failure to maintain the system can result in technical problems, which can compromise patient data and negatively affect the quality of care provided to patients.

EHR systems differ in functionality, usability, and data storage methods, which can result in data incompatibility between systems. This can lead to data fragmentation, making it challenging to share patient information between healthcare providers. In addition, the lack of standardization can cause challenges in training and onboarding staff, leading to inefficiencies in workflows.

The complexity of EHRs requires an understanding of information technology and computer systems, which many healthcare providers do not possess. Without this expertise, healthcare providers may not be able to fully utilize the features of EHRs, leading to inefficiencies and reduced quality of care. Moreover, the lack of technical expertise may also result in errors and mistakes, such as data entry errors, incorrect interpretations of information, and the failure to capture vital information.

Additionally, the lack of technical expertise among healthcare providers can also lead to resistance to the adoption of EHRs. Healthcare providers may be intimidated by the complexity of EHRs and the need to learn new skills and processes. This may result in a lack of enthusiasm and reluctance to use EHRs, which can hinder the adoption and utilization of these systems. Furthermore, healthcare providers who lack technical expertise may also be skeptical of the benefits of EHRs, leading to a lack of support for their implementation. This resistance can cause delays in the adoption of EHRs, ultimately affecting the quality of care provided to patients.

Finally, the lack of technical expertise among healthcare providers can also result in additional costs. Implementation of EHRs requires training, which can be costly, especially when healthcare providers need to be trained on a large scale. If healthcare providers do not have the necessary technical expertise to effectively use EHRs, the training costs can be even higher. Moreover, the lack of technical expertise may result in additional support costs, such as hiring IT professionals to troubleshoot issues with EHRs. These costs can be prohibitive for healthcare organizations, especially smaller ones, and can limit the adoption of EHRs and ultimately the quality of care provided to patients.

The successful implementation of an EHR system requires a supportive infrastructure that can accommodate the complexities of the system. This infrastructure includes the hardware and software components, as well as the technical and administrative support needed to maintain the system.

One critical element of supportive infrastructure for EHR adoption is the hardware and software necessary to run the system. The hardware includes servers, computers, and network devices that are essential to the operation of the EHR system. Additionally, software components such as electronic prescribing, clinical decision support, and patient portals must be integrated into the system. Healthcare organizations must ensure that the infrastructure can support the number of users, the amount of data, and the overall workload of the EHR system. This requires careful planning and investment in reliable hardware and software that can handle the demands of the system.

Another essential component of supportive infrastructure is the technical support necessary to maintain the EHR system. Healthcare organizations must have trained IT professionals on staff who can troubleshoot problems, maintain the system's security, and ensure that the system remains up to date with the latest software updates and security patches.

Workflow disruption refers to the fear that the adoption of EHRs will cause changes in established clinical workflows, which can potentially lead to inefficiencies, errors, and a decrease in the quality of care. This fear of disruption can prevent healthcare organizations from adopting EHRs, leading to missed opportunities for improving patient care and reducing costs.

The fear of workflow disruption can be attributed to several factors. First, clinical workflows are often deeply ingrained in healthcare organizations and are designed to meet the unique needs of patients and providers. The adoption of EHRs can disrupt these workflows, leading to confusion and resistance from providers. Second, EHRs often require significant changes to the way information is documented and shared among providers, which can be time-consuming and disrupt established communication channels.

II. METHODS

Ensemble voting classifier

Ensemble voting classifiers are a type of machine learning algorithm that combines multiple models to make a single prediction. The basic idea behind an ensemble classifier is that by combining the predictions of multiple models, we can improve the overall accuracy and reliability of the prediction. Ensemble voting classifiers work by taking the predictions of multiple base classifiers and combining them to make a final prediction. we first train multiple base classifiers on the same training data. The base classifiers can be of different types or use different algorithms and hyperparameters to generate their predictions. We then use these base classifiers to predict the class labels or probabilities of the test data. The predicted outputs of the base classifiers are combined using a voting mechanism, which takes the majority vote of the base classifiers as the final prediction. The voting mechanism can be of different types, such as hard voting, soft voting, or weighted voting. In hard voting, the final prediction is based on the majority vote of the base classifiers, while in soft voting, the final prediction is based on the weighted average of the predicted probabilities of the base classifiers. Weighted voting allows us to give more weight to the predictions of certain base classifiers that are more accurate or reliable.

Ensemble voting classifier can improve the overall performance of the classifier. This is because the different base classifiers are often good at different aspects of the classification task. For example, one classifier may be good at detecting patterns in the data, while another may be good at detecting outliers. By combining the predictions of these different classifiers, the ensemble voting classifier can improve its overall accuracy and reduce the risk of overfitting. The classifiers is that they are relatively easy to implement and can be used with a wide range of machine learning algorithms. This makes them a popular choice for many data scientists and machine learning practitioners. Additionally, ensemble voting classifiers can be trained using a variety of techniques, such as bagging, boosting, and stacking. These techniques can further improve the performance of the classifier and make it more robust to different types of data.

Stacking classifier

Stacking is a popular ensemble learning technique that combines the predictions of multiple base classifiers to generate more accurate predictions. A stacking classifier, also known as stacked generalization, is a meta-model that takes the outputs of multiple base classifiers and combines them using another classifier, called the meta-classifier. The main idea behind stacking is to leverage the strengths of individual base classifiers by combining their predictions in a way that reduces their weaknesses. Stacking can improve the accuracy and robustness of machine learning models, particularly in complex prediction tasks where individual models may not be able to capture all the relevant information.

To implement a stacking classifier, we first train multiple base classifiers on the same training data. The base classifiers can be of different types or use different algorithms and hyperparameters to generate their predictions. We then use these base classifiers to predict the class labels or probabilities of the test data. The predicted outputs of the base classifiers are combined using a meta-classifier, which takes the outputs as inputs and generates the final prediction. The meta-classifier can be of any type, such as a logistic regression, decision tree, or neural network. The meta-classifier is trained on the outputs of the base classifiers, which serves as input features. The training data for the meta-classifier is usually generated using cross-validation, where we split the training data into K folds and train the base classifiers on K-1 folds, and use the remaining fold as the validation set to generate the input features for the meta-classifier. We then repeat this process K times and aggregate the predictions of the meta-classifiers to generate the final prediction.

Label

Table 1. Label with classes

Healthcare Provider Class	Characteristics
Unwilling to Adopt EHR	- Hesitant due to concerns about the cost of implementation, privacy and security risks, or a general lack of technological knowledge. - May be resistant to change and prefer to stick to traditional paper-based records.
Undecided	- Open to the idea of adopting EHR, but may have concerns or reservations that are preventing them from making a decision. - Concerns may include the cost of implementation, training and support, and the potential for disruptions to patient care during the transition period.
Willing to Adopt EHR	- Eager to embrace the benefits of modern technology and actively seeking ways to integrate EHR systems into their practice. - Recognize the potential for increased efficiency, improved patient outcomes, and enhanced data sharing capabilities.

Healthcare providers may find themselves in one of three classes when it comes to adopting EHR systems: unwilling to adopt EHR, undecided, or willing to adopt EHR. The first class, those who are unwilling to adopt EHR, may be hesitant due to concerns about the cost of implementation, privacy and security risks, or a general lack of technological knowledge. Healthcare providers in this category may also be resistant to change and prefer to stick to traditional paper-based records. The second class, those who are undecided, may be open to the idea of adopting EHR, but may have concerns or reservations that are preventing them from making a decision. These concerns may include the cost of implementation, training and support, and the potential for disruptions to patient care during the transition period. On the other hand, the third class, those who are willing to adopt EHR, are eager to embrace the benefits of modern technology and are actively seeking ways to integrate EHR systems into their practice. They recognize the potential for increased efficiency, improved patient outcomes, and enhanced data sharing capabilities.

III. RESULTS

The results in table 1, 2, 3, and 4 present the accuracy of four models for classifying individuals into three categories based on their willingness to adopt Electronic Health Records (EHR): Unwilling to adopt EHR, Undecided, and Willing to adopt EHR. The first table shows the Ensemble Voting Classifier's performance, where three models were combined to make predictions. The accuracy of the Logistic Regression and Naive Bayes models was 0.7, while that of Random Forest was 0.57. The ensemble achieved an accuracy of 0.69. The confidence interval of the accuracy was narrow, indicating that the results were statistically significant. However, the performance of Random Forest was relatively poor compared to the other two models.

Table 2 shows the results of the Stacking classifier, where the three models were trained on the data, and their predictions were then combined by a meta-classifier. The accuracy of Naive Bayes was 0.65, while that of Random Forest was 0.57. KNN performed the worst, with an accuracy of 0.56. The Stacking Classifier achieved an accuracy of 0.58. The confidence interval was also relatively wide, indicating that the results were not statistically significant.

Table 3 shows the results of the Ensemble Voting Classifier with additional features. The three models were trained on the original features and the additional ones. The accuracy of Logistic Regression was 0.82, while that of Naive Bayes was 0.79. Random Forest performed relatively poorly, with an accuracy of 0.74. The ensemble achieved an accuracy of 0.82. The standard deviation of the accuracy was relatively low, indicating that the results were statistically significant. The addition of features seemed to improve the performance of Logistic Regression and Naive Bayes models.

Table 4 shows the results of the Stacking Classifier with additional features. The accuracy of Naive Bayes was 0.79, while that of Random Forest was 0.72. KNN performed relatively poorly, with an accuracy of 0.68. The Stacking Classifier achieved an accuracy of 0.69. The standard deviation of the accuracy was relatively low, indicating that the results were statistically significant. The addition of features seemed to improve the performance of the Naive Bayes and Random Forest models.

The Ensemble Voting Classifier with additional features outperformed all other models, achieving an accuracy of 0.82. The results of the Ensemble Voting Classifier without additional features and Naive Bayes with additional features were also promising, achieving accuracies of 0.69 and 0.79, respectively. The poor performance of Random Forest in some cases indicates that this model may not be the best choice for this classification task. The addition of features seemed to improve the performance of some models, especially Logistic Regression and Naive Bayes. However, the performance of the Stacking Classifier was relatively poor compared to other models, indicating that this approach may not be suitable for this classification task. The results of this study suggest that the Ensemble Voting Classifier with additional features is a promising model for classifying individuals based on their willingness to adopt EHR.

Table 1. Ensemble Voting Classifier

Model	Accuracy	95% Confidence Interval
Logistic Regression	0.7	+/- 0.02
Random Forest	0.57	+/- 0.11
Naive Bayes	0.7	+/- 0.07
Ensemble	0.69	+/- 0.03

Table 2. Stacking classifier

Model	Accuracy	95% Confidence Interval
KNN	0.56	+/- 0.03
Random Forest	0.57	+/- 0.08
Naive Bayes	0.65	+/- 0.02
Stacking Classifier	0.58	+/- 0.05

Figure 1. Ensemble Voting Classifier classification region

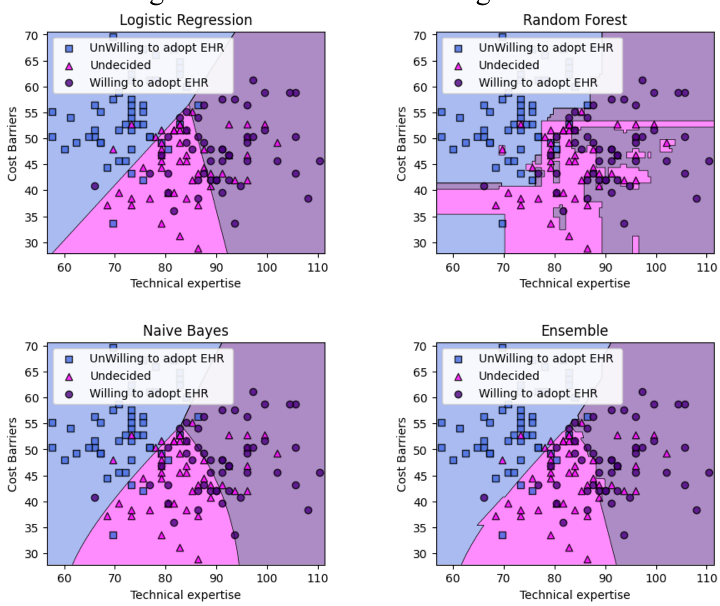


Figure 2. Stacking classifier classification region

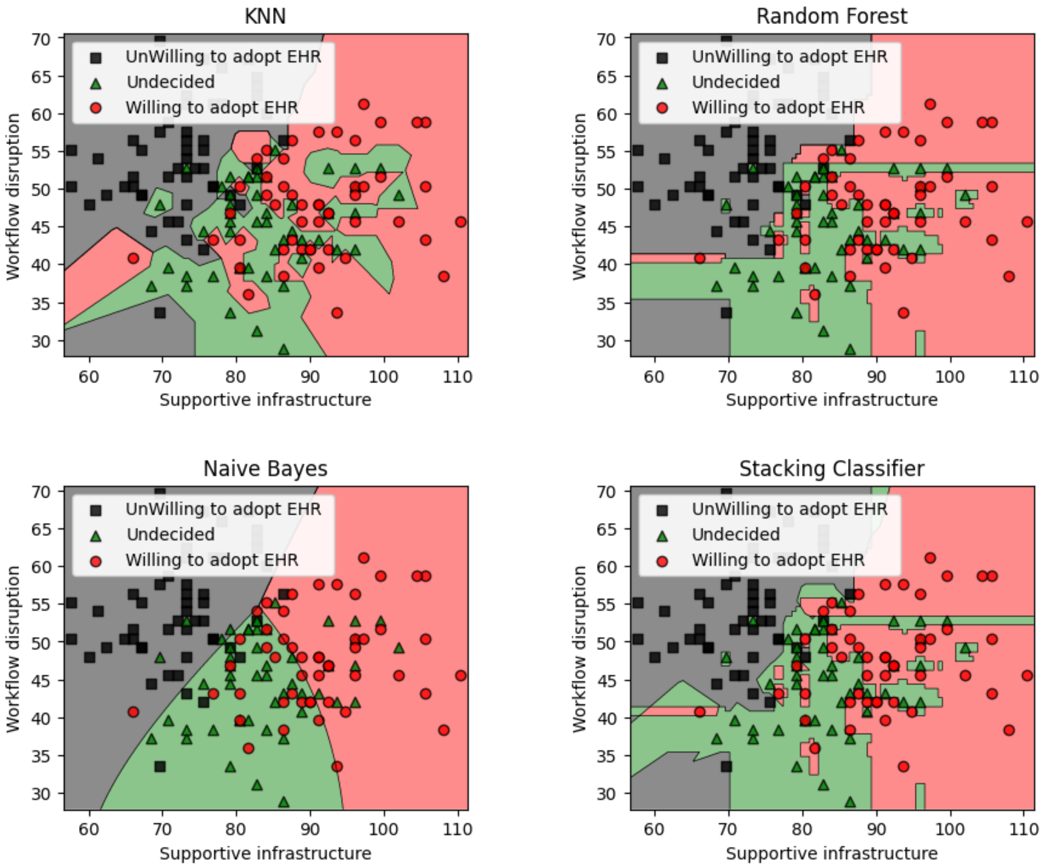


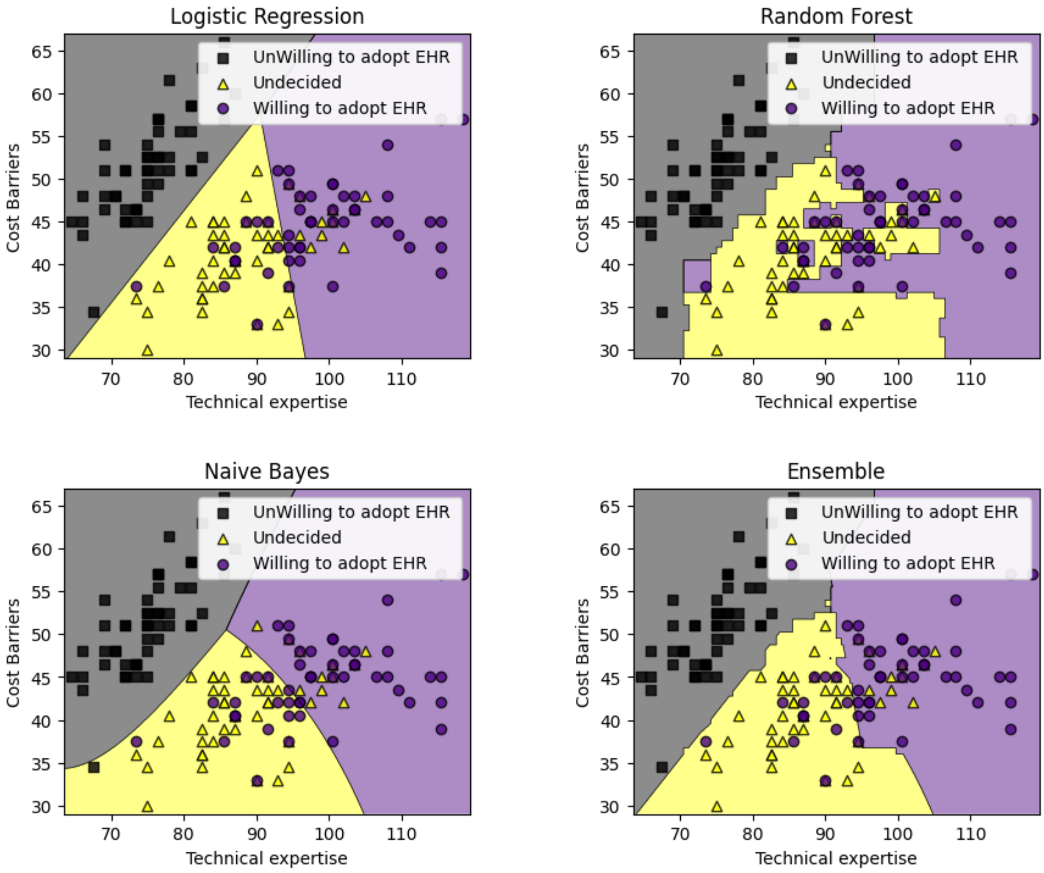
Table 3. Ensemble Voting Classifier with additional features

Model	Accuracy	Standard Deviation
Logistic Regression	0.82	+/- 0.06
Random Forest	0.74	+/- 0.04
Naive Bayes	0.79	+/- 0.05
Ensemble	0.82	+/- 0.06

Table 4. Stacking classifier with additional features

Model	Accuracy	Standard Deviation
KNN	0.68	+/- 0.02
Random Forest	0.72	+/- 0.03
Naive Bayes	0.79	+/- 0.04
Stacking Classifier	0.69	+/- 0.02

Figure 3. Ensemble Voting Classifier classification region with additional features

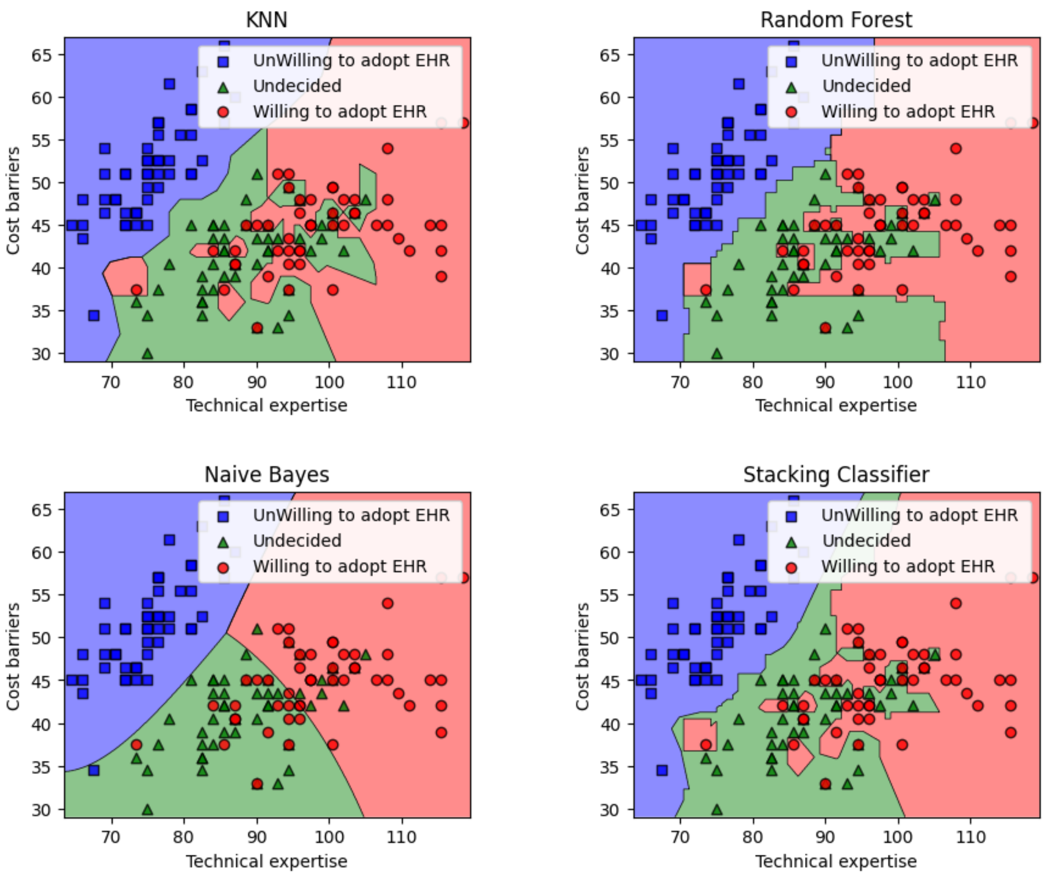


Healthcare centers with supportive infrastructure are more likely to adopt EHR due to the ease of implementing EHR technology. The adoption of EHR technology has become a top priority for healthcare centers, and those with supportive infrastructure are better positioned to benefit from this technology.

Moreover, healthcare centers with a supportive IT culture are more likely to have staff who are comfortable working with technology and can embrace EHR as a critical tool in improving patient care. EHR technology requires a shift in mindset and a willingness to adapt to new processes. Staff who are familiar with technology can easily understand the benefits of EHR and how it can improve their workflow. This results in a smooth transition to EHR and ensures that staff are well-trained and equipped to use the technology effectively. In contrast, healthcare centers without a supportive IT culture may face challenges in adopting EHR, resulting in delays and difficulties in implementing the technology.

Additionally, healthcare centers that have invested in modern IT infrastructure are better positioned to adopt EHR and benefit from the technology's many advantages, including improved patient safety, increased efficiency, and reduced costs. Fast internet connection speeds and robust hardware can improve the efficiency of EHR implementation and usage.

Figure 4. Stacking classifier classification region with additional features



Secure data storage capabilities are essential for maintaining the confidentiality of patient records. The adoption of EHR technology can also result in cost savings by reducing paperwork and the need for physical storage space. Overall, healthcare centers with supportive infrastructure can leverage EHR technology to improve patient outcomes, enhance their services, and reduce costs.

Healthcare centers have remained hesitant to adopt the technology due to the fear of workflow disruption. EHR implementation can lead to significant changes in a healthcare center's workflow, which can cause uncertainty and resistance to the adoption of this new technology. There are concerns about the impact on staff, patient care processes, and the possibility of technical glitches during implementation.

One significant concern with EHR adoption is the need to train staff to use new technology. Staff members may be comfortable with the traditional paper-based systems, and the transition to digital records can be overwhelming. Staff training is necessary to ensure that healthcare providers are equipped with the skills and knowledge required to use the new system effectively. This process can be time-consuming and may take away from time that providers would typically spend on patient care. Furthermore, healthcare providers may be concerned about the potential for lost productivity during the transition period.

Additionally, healthcare centers may need to adjust patient care processes to align with the EHR system. This change may cause temporary delays in patient care, and providers may need to spend more time documenting patient information than usual. The new system's integration can also lead to technical glitches that may require additional support, which can cause further delays. These concerns may make healthcare providers hesitant to adopt the new system, as the temporary impact on patient care may seem like too significant a risk.

Healthcare centers with technical expertise are more willing to adopt EHRs due to their ability to navigate the complexities of the system and utilize its full potential.

Technical expertise refers to the proficiency of healthcare professionals in using technology for healthcare-related activities. Healthcare centers with technical expertise are more familiar with the technical aspects of EHRs, such as data storage and retrieval, security measures, and data analysis. As a result, they are better equipped to implement EHRs and leverage their benefits. Healthcare centers with technical expertise are also better equipped to handle any technical glitches or system failures that may occur, minimizing the impact on patient care.

In addition, healthcare centers with technical expertise tend to have a more tech-savvy staff. These staff members are more receptive to using EHRs and more likely to embrace the change that comes with adopting new technology. They can also provide training to other staff members who may be less familiar with the system, making the transition smoother and more efficient. Overall, healthcare centers with technical expertise are better positioned to adopt EHRs and achieve the benefits that come with them.

The cost of implementing and maintaining EHR systems can be a major barrier for healthcare providers, especially smaller clinics and private practices. The initial investment in hardware, software, and training can be significant, and ongoing maintenance costs can add up over time. These costs can deter healthcare providers from adopting EHR systems, which in turn can impact patient care and outcomes.

The cost of EHR implementation and maintenance can be particularly challenging for smaller healthcare providers. These providers may not have the same financial resources as larger hospitals and healthcare systems, making it more difficult for them to invest in EHR systems. Additionally, smaller providers may not have the same level of technical expertise or support staff as larger providers, which can make it more difficult for them to manage and maintain their EHR systems. These challenges can result in a reluctance to adopt EHR, which can limit access to critical patient information and impact the quality of care provided.

IV. CONCLUSION

The cost of EHR implementation can create a significant barrier for healthcare providers, especially those with limited financial resources. The high cost of EHRs can also discourage healthcare providers from adopting the technology, resulting in a digital divide that can have serious implications for patient care. The cost of maintenance and upkeep is an ongoing concern that requires healthcare providers to allocate resources continually. The lack of technical expertise among healthcare providers is a significant barrier to the adoption and effective utilization of EHRs. One strategy to overcome this challenge is to pursue government incentives and grants for EHR adoption. Providers can also apply for grants from federal and state agencies or private organizations. Additionally, healthcare organizations can consider partnering with other providers or sharing EHR systems to reduce costs. Another strategy to overcome the cost barrier is to prioritize long-term cost savings by investing in high-quality EHR systems. While initial implementation costs may be high, investing in a robust EHR system with advanced features can lead to significant cost savings in the long run. For example, a well-designed EHR system can reduce administrative costs, improve billing accuracy, and minimize the need for paper-based records. Healthcare providers can also consider cloud-based EHR systems, which eliminate the need for costly hardware and maintenance and provide greater flexibility in terms of scalability.

This lack of expertise can lead to inefficiencies, resistance to adoption, and additional costs. Healthcare organizations must prioritize the training of their staff to ensure that they have the necessary technical skills to use EHRs effectively and efficiently. The successful implementation of an EHR system requires a supportive infrastructure that includes hardware and software components, technical support, and administrative support. Healthcare organizations must invest in the necessary resources and personnel to ensure that their EHR system functions at optimal levels and provides the maximum benefit to both patients and staff. Training programs should be designed to equip staff with the necessary technical skills to use EHRs effectively and efficiently. Organizations can also consider partnering with EHR vendors to provide ongoing training and support. Additionally, healthcare providers can recruit and hire staff with relevant technical skills to fill critical roles in EHR implementation and maintenance.

The fear of workflow disruption is a common barrier to the adoption of EHRs in healthcare organizations. The adoption of EHRs can lead to changes in established clinical workflows, which can cause inefficiencies, errors, and a decrease in the quality of care. However, this fear can be overcome through careful planning, communication, and involvement of stakeholders. Healthcare organizations can engage stakeholders, including physicians, nurses, and administrative staff, throughout the implementation process to identify potential workflow issues and develop solutions collaboratively. Additionally, organizations can conduct workflow assessments to identify areas for improvement and optimize the EHR system to support existing workflows. This approach can minimize the disruption to established clinical workflows and ensure that the EHR system is effectively integrated into the healthcare organization's operations.

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