

Small clinic appointment scheduling and management

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Abstract

The "Doctor Appointment System" has been developed to override the problems prevailing in the practicing manual system. This software is supported to eliminate and, in some cases, reduce the hardships faced by this existing system. Moreover, this system is designed for the particular need of the company to carry out operations in a smooth and effective manner. The application is reduced as much as possible to avoid errors while entering the data. No formal knowledge is needed for the user to use this system. Thus, by this all it proves it is user-friendly. Doctor Appointment System, as described above, can lead to error free, secure, reliable and fast managementsystem.

Keywords—component, formatting, style, styling, insert

I INTRODUCTION

In the last decades, artificial intelligence took place in the medical field and machine learning algorithms can work as a efficient tool to understand the patients behavior and to achieve better medical appointment allocation in scheduling systems. Every organization, whether big or small, has challenges to overcome and managing the information of Appointment, Doctor, Booking, Doctor Fees, Doctor Schedule. Every Doctor Appointment System has different Doctor needs, therefore we design exclusive employee management systems that are adapted to our managerial requirements. Doctor Appointment System, as described above, can lead to error free, secure, reliable and fast management system. It can assist the user to concentrate on their other activities rather to concentrate on the record keeping.

The organization can maintain computerized records without redundant entries. That means that one need not be distracted by information that is not relevant, while being able to reach the information.

II IMPLEMENTATION OF MODULES

This project includes the following modules:

- Data processing
- Deep neural network model and its training

- Data missingness and missingness indicator
- Supervised learning-based data imputation
- Interpretation of prediction model

1. Data Processing

Data Processing is the task of converting data from a given form to a much more usable and desired form i.e. making it more meaningful and informative. The output of this complete process can be in any desired form like graphs, videos, charts, tables, images, and many more, depending on the task we are performing and the requirements of the machine.

The main steps involved in data processing are:

1.1 Data cleaning: This step involves identifying and removing any missing, duplicate, or irrelevant data. This step is important because incorrect or inconsistent data can negatively impact the performance of the ML model.

1.2 Data transformation: This step involves converting the data into a format that is suitable for modeling. This can involve normalizing the data, converting categorical data into numerical data, and reducing the dimensionality data.

1.3 Data preparation: This step involves splitting the data into training and testing datasets. The training dataset is used to train the ML model, while the testing dataset is used to evaluate the performance of the model. It is important to note that the data processing step can have a significant impact on the performance of the ML model, so it is important to carefully consider the steps involved and ensure that the data is prepared properly.

2. Deep neural network model and its training

Deep neural networks are a powerful category of machine learning algorithms implemented by stacking layers of neural networks along the depth and width of smaller architectures. Deep networks have recently demonstrated discriminative and representation learning capabilities over a wide range of applications in the contemporary years. Researchers in ML are expanding the horizons of deep learning by seeking their prospective applications in other diverse domains. One such forthcoming domain is marine scene classification.

3. Data missingness and missingness indicator

There can be multiple reasons why certain values are missing from the data. Reasons for the missing of data from the dataset affect the approach of handling missing data. So, it's necessary to understand why the data could be missing.

- Some of the reasons are listed below:
 - Past data might get corrupted due to improper maintenance.
 - Observations are not recorded for certain fields due to some reasons. There might be a failure in recording the values due to human error.
- The user has not provided the values intentionally

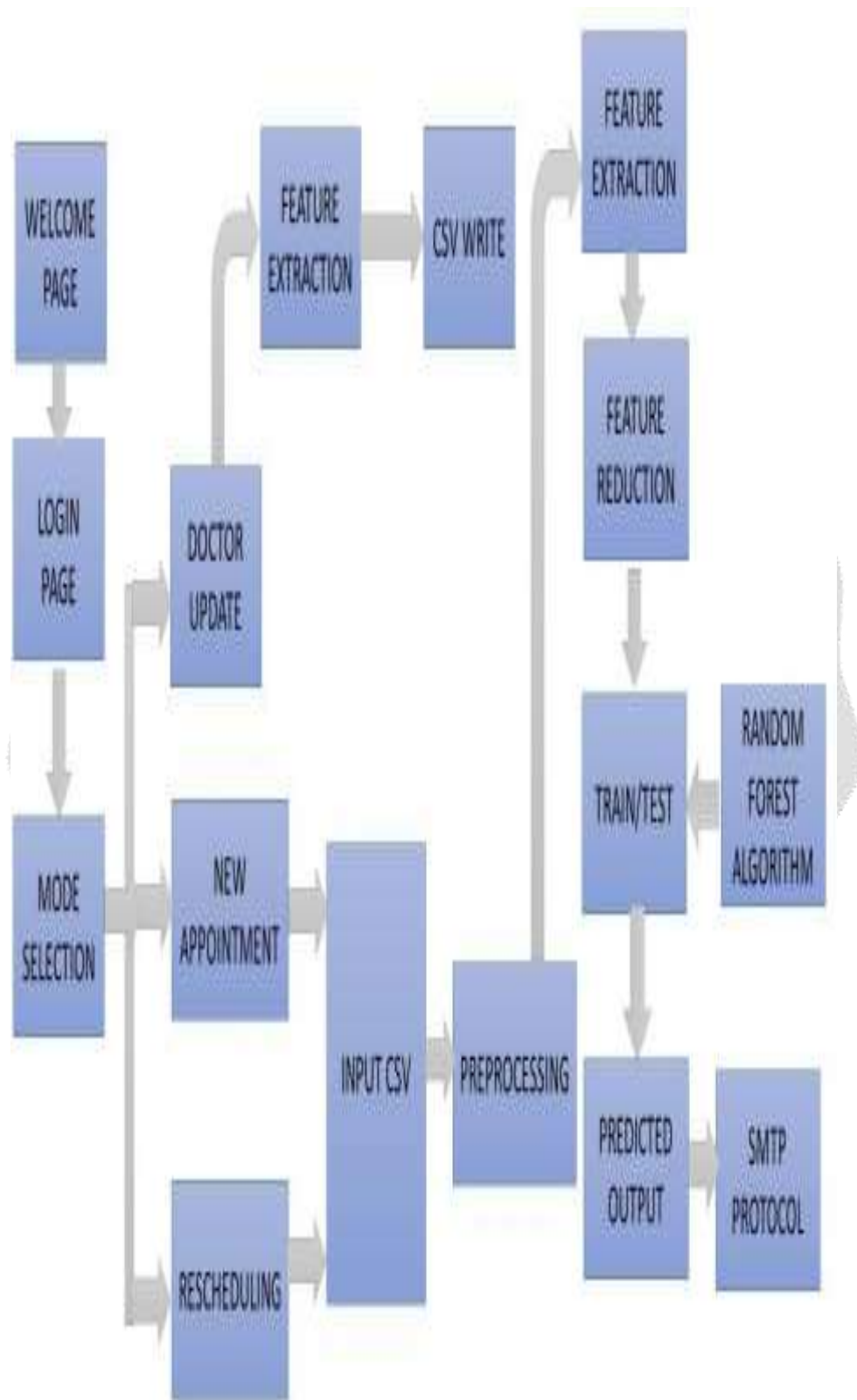
4. Supervised learning-based data imputation

Data imputation is a method for retaining the majority of the dataset's data and information by substituting missing data with a different value. These methods are employed because it would be impractical to remove data from a dataset each time. Additionally, doing so would substantially reduce the dataset's size, raising questions about bias and impairing analysis.

5. Interpretation of prediction model

- Our project has gained the essential outputs necessary for each phases.
 - The first phase is for the doctor to enter the patient's details and store it in csv file. Hence the data is saved successfully for future reference.
 - The second phase is for the new patients to fill their details and booking their appointments. The appointment date is got and is sent to the concerned using smtp protocol.
 - The third phase includes the patient's rescheduling.

III ARCHITECTURE DESIGN



The data of medical appointments were collected from the outpatient clinic of a major academic pediatric hospital for a quality improvement purpose. The data contain appointments of all departments and visit types of the clinic. All categorical data types are converted to multiple binary variables, where 1 and 0 indicate the presence and absence, respectively, of each feature. For example, the feature “day of the week of the appointment” originally has values from 1 to 7, representing Sunday to Monday of the week. In our analysis, we converted the feature to seven separate binary indicators with 1 indicating that the appointment is made on that day of the week. All numerical features were normalized so that they lie between 0 and 1. The labels are binary digits, where 1 and 0 denote no-shows and shows, respectively, at the corresponding appointment. A single patient may have more than one records due to multiple appointments. The vast majority of the patients are children and often come to the appointments with their parents or caregivers. All patients have an appointment status recorded. We conducted a binary classification to predict if a patient will have a “no show”. Patients with certain medical conditions for which this hospital has unique expertise on continue to seek healthcare in institution.

CONCLUSION

Patient-related information, including age, gender, previous visit rate, fund, etc., was used as input to train a machine learning model aimed at predicting the risk of a patient’s no-show at the time when the appointment was scheduled. Given how common patients’ records contained missing information (about 77% of the records) in our data, we designed methods that are capable of handling this via data missingness indicators strategies (refer to the Method subsection for details). As a reference, to motivate the need for a more sophisticated modeling technique to tackle this problem, we also include the predictive performance results of a simple logistic regression approach in the Supplementary materials. In order for our methods to capture the potential non-linear relationships among different features and our desired outcome, we used a neural network approach. Predictive performance of our model was evaluated in a collection of observations not used to train our models, that is, in a strictly out-of-sample fashion

REFERENCES

- [1]. Pereira, F.; Crocker, P.; Leithardt, V.R. PADRES: Tool for PrivAcy, Data Regulation and 377 Security. *SoftwareX* 2022, 17.
- [2]. Batool, T.; Abuelnoor, M.; El Boutari, O.; Aloul, F.; Sagahyroon, A. Predicting hospital no-shows using machine learning. *2020 IEEE International Conference on Internet of Things and Intelligence System (IoT&IS)*. IEEE, 2021.
- [3]. Ahmad, M.U.; Zhang, A.; Mhaskar, R. A predictive model for decreasing clinical no-show rates in a primary care setting. *International Journal of Healthcare Management* 2021.
- [4]. Nasir, M.; Summerfield, N.; Dag, A.; Oztekin, A. A service analytic approach to studying patient no-shows. *Service Business* 2020.
- [5]. Abu Lekham, L.; Wang, Y.; Hey, E.; Lam, S.S.; Khasawneh, M.T. A multi-stage predictive model for missed appointments at outpatient primary care settings serving rural areas. *IISE Transactions on Healthcare Systems Engineering* 2021.