Impact of Big Data on Digital Transformation in 5G Era

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Abstract. One of the potential top-level goals for 5G heterogeneous networks may be intellectual and perfect network which modifies consumer preferences in a proactive manner in addition to needs of channel. Research provides an interdisciplinary approach to e-health, primarily concern BDA, and radio space management inside a various level fifth generation network in the company of massive data. The growing need for and usage of big data fuelled digital transformation. The research focuses on the effect of Big Data on digital technologies during the 5G era. To carry out digital transformation, three machine learning (ML) algorithms are identified. In addition to decision tree DT the other algorithms used for the classification are NB, LR. These algorithms run on the large data processing engine they work. These algorithms serve as an ensemble tool for examining old records of stroke outpatients (OPs) and body built IOT based sensors [19]. These readings are available as Big Data. In the model which has been proposed here, OP-Centric Network Optimization Framework was presented before evaluating the machine learning algorithm function and all appropriate steps to plan massive data. An ensemble method in the company of NB classification device, decision tree classification device, and logistic classification device was used in this analysis. These entire classification devices are highly controlled and managed classification device. This method is based on the OP data set and feeds the predicted stroke probabilities to an SV classifier.

1. Introduction

Research takes into account the effect of big data on the digital revolution in the 5G period. Patient data is regarded as big data in this study. This data have been analysed by algorithms for machine learning. Different Bayesian naïve algorithms are used for decision-making, logistic regression and decision tree. This paper addressed the efficiency factors of 5G and 6G. In addition, the OP-Centric Network Optimization Framework is presented.

1.1. 5G

5G came in to existence in the form of conventional mobile network technology of fifth generation that wireless phone operators started implementing globally in the year of two thousand and nineteen. It came in to existence in the form of proposed replacement of fourth generation networks that link the majority of today's cell phones. According to the GSM Association, by 2025, 5G networks will have over 1.7 billion users worldwide. 5G networks, as their ancestors, are wireless. In such type of system coverage sector is separated in cells. Fifth generation devices which are wireless has been connected in the company of electronic telecommunications systems through radio waves with the help of local
antenna. Most significant benefit of the modern networks is their increased bandwidth, which makes for faster transmission rates, initially reaching ten gigabits in one second. 4G phones are unable to connect to emerging networks that need 5G cellular equipment.

1.2. 6G
6G is the sixth generation telecommunications specification that is now being designed for cellular network systems. It is the intended counterpart to 5G which is probably even faster. Like their contemporaries, 6G networks will most definitely be broadband cellular networks with service regions divided into small geographic cell areas. Several companies (Nokia, Ericsson, Huawei, Samsung, LG, Xiaomi, and Apple) were interested in 6G and countries (China, Japan, and Singapore).

2. Factor influencing performance of 5G and 6G
5G and 6G both plunged simultaneously onto the tech scene. 6G Research and Development (R&D) programmers began marketing around the same period as 5G. There will be any confusion on the difference between the two. Here are five items you need to know.

- 5G and 6G Use two different spectrum components: 5G and 6G also utilize higher radio frequencies to transmit more data quicker. 5G instead utilizes wireless frequencies in sub-6 gigahertz (GHz) and in excess of 24.25 GHz respectively called low-band frequencies and high-band frequencies. 6G will operate at 95 GHz to 3 terahertz frequencies (THz). 6G can emit 1,000 times the speed of 5G at certain wavelengths (which is only four to five times faster than 4G).

- 5G Enables the Internet of Things, 6G Speeds it up: much of the hype about 5G comes from the idea that the Internet of Things will become a practical everyday reality eventually. The 4G channels are too limited to transmit data at the rates required by intelligent devices for optimum operation. That’s why they didn’t gain traction. This would be improved with 5G and certainly with 6G again.

- 5G would not substitute 4G, 6G won't substitute 5G: Although 4G is just a stronger 3G variant, 5G and 6G are different wireless networking variants. Several predictions indicate that 6G will be used mostly for business, military and industrial uses with some consumer applications, such as immersive entertainment. Any system stream with 6G would not be practicable, but other developments will change that.

- 6G Opens New Connectivity Frontiers but 5G Doesn't: According to the infrastructure conditions, 5G could not launch. In contrast, 6G will build on the 5G networks and increase connectivity – both on land, under the sea and in space.

- All generations have very low latency: latency is the length of time a data packet requires for a frequency to connect. The 4G delay is around 50 msec. In 5G, the period is decreased to a factor of ten (5 milliseconds). The latency of 6G is estimated to be 1 millisecond, five times short as the latency of 5G. Due to the near instantaneous level, huge data transfers can be made feasible.

- 4G vs. 5G vs. 6G: More than just wireless technology developments: 6G implies, while available, more than slower speeds and more data transmission. When we equate wireless 4G and 5G technologies, we will see the evolution of wireless technology. Comparing 5G to 6G makes things more complicated, but it may be that the system is just a decade out.

3. Role of Big Data analytic in 5G Era
We should anticipate a lot of businesses to spend more in big data and analysis as we hit 5G. IDC reports in one survey that the average rate of eleven point seven percent of CAG would increase worldwide sales for the large data and market analysis by over EUR 203 billion in 2020. As such, the use of data analytics is agile and stable. Although analytics will continue to do its primary task - to obtain insights into the vast universe of Data for improved ROI, analytics will probably play advanced roles in helping companies expand.

4. Research Methodology
Present analysis is an experiment that takes into account the impact of Big Data on digital transition. This digital transition is expected to be the impetus for the 5G network. Research provides an interdisciplinary approach toe-health, primarily concern BDA, and radio space management inside a various level fifth generation network in the company of massive data. The digital transition was motivated by the increasing need for and utilization of large data. The thesis explores the impact of large data in the 5G era digital transformation. For digital transformation, three machine learning (ML) algorithms are taken into account. In addition to decision tree DT the other algorithms used for the classification are NB, LR. These algorithms are used in the major data processing engine. These algorithms are used as part of an ensemble method to investigate the medical history of stroke outpatients and the lectures from IOT sensors [20-23].

5. Proposed Framework for OP-centric network optimization
Here, the framework form is presented by us ahead of delving into ML method. This section ends with the formulation of the problem, in which the major mathematical equations relating to objective functions and restrictions are added.

5.1. System Model
We assume in this paper that a HetNet condition consists of an urban MB station and two neighbouring stations.

![Diagram](Figure 1. Out-Patient priority calculation procedure)

The MBS has a coverage area of three hundred to six hundred meters, while the PB station possesses the distance in between forty to hundred meters. It was assumed by us in one of the earlier article [4], that a spectrum partitioning technique[10] was used for reducing effect of MBS users’ inter-tier interference on PB station users. In this essay, we look at the consequences of interference. As seen in
figure two, a BDA sixth generation mixed network situation, users are divided into two groups: nice (standard) users and OPs. As in the real universe, users are uniformly distributed at varying distances around the base stations, resulting in different energy collections from the attached UEs at the base point. When a low-level SINR channel is used in a procedure, the health care provider cannot be contacted in the case of an emergency, resulting in a delayed response. In this case, a stroke patient loses almost two million neurons in every sixty seconds ahead of therapy begins [1]. As a result, the basic intention is the provision high-gain PRBs in the direction of OPs on the basis of medical condition seriousness. It means on the basis of Heart attack risks and chances of its occurrence. Inside those BDA engine which are based on cloud, above is calculated using the approach seen in Fig. 3. Prioritized OPs would have higher spectral performance than average users because of higher SINR values. This would result in increased production because output increases with the increment of spectral performance. This will ensure that data is sent by OPs in a very quick manner.

5.2. ML Method
In this paper, a fixed approach that consists of three supervised classification device is used by us. These classification devices are NB classification device, DT classification device, and LR classification device, which function over OP data. It feed the chances of estimated stroke in the direction of SV classification device. If a certain characteristic vector is present, any of the previous classificatory gives a likelihood of stroke (representing the current condition of the OP). In the company of group learning, it becomes possible to combine such classification device more effectively into an individual prediction form, increasing confidence in the predicted result.

6. Results and Discussion
In table one a single OP dataset snapshot is demonstrated. As mentioned in [13], BP, Cholesterol and Smoking have been considered main contributors to a stroke and are distinguished by f1 to f4 characteristics. The cardiovascular cohort study in Framingham [11] is used to supplement the human surgery dataset. Framingham's study involves lectures by more than 3000 individuals. As a result of legal and privacy considerations, we were unable to access medical reports from many individuals. Consequently, Framingham dataset parts are segmented for representing numerous OPs.

| Day | Overall Cholesterol f1 | Upper Blood pressure f2 | Lower Blood pressure f3 | Rate of Smoking f4 | Stroke C |
|-----|------------------------|-------------------------|-------------------------|-------------------|----------|
| 1   | High                   | Average                 | Higher Hypertension     | Controlled        | Yes      |
| 2   | Normal                 | Pre-Hypertension        | Lower                   | Uncontrolled      | No       |
| *   | *                      | *                       | *                       | *                 | *        |
| 200 | Perfect                | Higher Hypertension     | Pre-Hypertension        | Light             | No       |

(A) (current state )

| Day | F1   | F2             | F3            | F4             | C  |
|-----|------|---------------|--------------|---------------|---|
| 1   | Average | Pre-Hypertension | Average | Uncontrolled | ?   |

Ranges in Table I (A), it has been considered as subset of them in Table II. To be as medically descriptive as possible, the distinct values of f1...f3 correspond to government health agencies or public entities 13-14. F4 allows use of the ranges in [14].
Table 2. Values of feature and level that are corresponding

| Feature                | Range                                      | Level                |
|------------------------|--------------------------------------------|----------------------|
| Total cholesterol Level (mg/dl) [13] | Less than two hundred                      | Maximum_ Level       |
|                        | In between two hundred and two hundred and thirty nine | Average_ Level       |
|                        | 240+                                       | Higher_ Level        |
| Systolic BP (mmHg) [12] [14] | Less than one hundred and twenty          | Average_ Level       |
|                        | 120-139                                    | Pre-hypertension_ Level |
|                        | 140+                                       | High- hypertension_ Level |
| Diastolic BP (mmHg) [13] | Less than eighty                           | Average_ Level       |
|                        | In between eighty to ninety                | Pre-hypertension_ Level |
|                        | 90+                                        | Higher- hypertension_ Level |
| Smoking rate (Cig/Day) [14] | In between one to ten                      | Light_ Level         |
|                        | In between eleven to nineteen             | Controlled_ Level    |
|                        | 20+                                        | Uncontrolled_ Level  |

The statistical [17] significance of the characteristics is examined by displaying P-values of 0.05, as seen in Table III. As a result, the zero hypothesis that adopt characteristics are unrelated to stroke could be rejected.

Table 3. Feature values & P-values that are corresponding to them

| Out patient Dataset | P- Value     |
|---------------------|--------------|
|                     | Cholesterol | Systolic BP | Diastolic BP | Smoking Rate |
| OP# 1               | 0.00251      | 0.000021867 | 0.000012957 | 0.000000645 |
| OP# 2               | 0.0122       | 0.000071185 | 0.000006144 | 0.000000042 |
| OP# 3               | 0.00215      | 0.000030752 | 0.000007516 | 0.000000042 |

6.1. NB Classification Devices
To predict the probability of a case c, the NB classifier uses multiple separate functional variables derived from a historical dataset. Since it believes that the function variables are identical, the classifier is referred to as naive. I track records for disease risk prediction since (iii) it is suitable for any two-grade definition with minimal characteristics, (iv) it is demonstrated in cardio-vascular (CVD) prediction relative to other methods, and (v) no significant training data is needed.

6.2. LR Classification Devices
The primary differences in the middle of this and upper classifiers are that the NB classifier is faster and can generate a noticeable shift in response to the function vector. This indicates, however, that the function vector values are especially vulnerable. As seen in the classifier, it is a basic method for disease prediction. The logistics model is focused on the logistics position that has been established (3). If x is negative, this equation equals zero. If x is positive, this equation equals one.

6.3. Decision Trees Classifier
For the DT process, the dataset is divided into subsets. The division begins with a series of sequential sections with subdivisions. The idea behind tree methods is to use the appropriate class with a number of partitions. The partitioning is performed to choose splits of leaves that are purer than the parent node. By grouping vectors from the root of the tree to certain leaf nodes, DT classifies them. Any node in this tree defines a test for some input vector property, and each branch that descends from that node
represents one of the possible values for that function. The reasons for using DTs are as follows: (i) it has the ability to select features or filter variables indirectly, (ii) it is simple to learn, analyses, and show, (iii) nonlinear associations between parameters [18] have little effect on tree efficiency, and (iv) it has a track record in the literature on stroke prediction as shown in [11, 12]. The pureness is calculated using a Gini rating, which is an attribute variable that assigns a score to each attribute. The binary division criterion that results in the greatest reduction in impurities (i.e. the greatest value in information) is selected.

6.4. Classifier Comparison and Evaluation

Accuracy: - The relationship between TP and data TN is described and shown below. Accuracy [15] measures how well the classifier predicted whether an occurrence happened or not.

\[
Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100\%
\]

Sensitivity: - True Positive Rate or Memory is described in the form of classifier's capability to select event of interest. As a result, the real positive values are properly labelled as TP (i.e., stroke=1) and are mentioned below. Classifier's capability to categorize individual as a danger has been tested.

\[
Recall = \frac{TP}{TP + FN} \times 100\%
\]

Precision: - As well as constructive and predictive value (PPV) does this answer the question of how many of the citizens we expected will be in danger? That is also the proportion of accurate optimistic forecasting of overall chances classified vectors.

\[
Precision = \frac{TP}{TP + FP} \times 100\%
\]

F1 Score: - Identified according to the consistency and recall values. This ranking tests the equilibrium between consistency and reminder, where the first emphasizes real positive and the second focuses on real bad factors. It then has the same weight and reminder as the harmonic mean of both as seen below.

\[
F1\ Score = \frac{2 \cdot \text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}
\]

| Classifier | OP# 1 Dataset used for Training | OP# 2 Dataset used for Training | OP# 3 Dataset used for the Training |
|------------|---------------------------------|---------------------------------|-----------------------------------|
| NB         | Accuracy: 80.0, Recall: 75.0, Precision: 89.0, F1-Score: 83.0 | Accuracy: 76.8, Recall: 67.0, Precision: 78.0, F1-Score: 73.0 | Accuracy: 81.5, Recall: 74.0, Precision: 85.0, F1-Score: 78.0 |
| LR         | Accuracy: 88.0, Recall: 85.0, Precision: 93.0, F1-Score: 89.0 | Accuracy: 79.0, Recall: 74.0, Precision: 80.0, F1-Score: 78.0 | Accuracy: 79.0, Recall: 66.0, Precision: 89.0, F1-Score: 75.0 |
| DT         | Accuracy: 90.0, Recall: 89.0, Precision: 95.0, F1-Score: 90.0 | Accuracy: 79.0, Recall: 66.0, Precision: 89.0, F1-Score: 75.0 | Accuracy: 79.0, Recall: 66.0, Precision: 89.0, F1-Score: 75.0 |
| SV         | Accuracy: 90.0, Recall: 88.0, Precision: 94.0, F1-Score: 90.0 | Accuracy: 81.5, Recall: 74.0, Precision: 85.0, F1-Score: 78.0 | Accuracy: 79.0, Recall: 66.0, Precision: 89.0, F1-Score: 75.0 |
### OP#1 Training Dataset

| Classifier | Accuracy | Recall | Precision | F1-Score |
|------------|----------|--------|-----------|----------|
| NB         | 86.6     | 75.0   | 89.0      | 84.0     |
| LR         | 90.0     | 89.0   | 87.0      | 89.0     |
| DT         | 91.0     | 85.0   | 96.0      | 90.0     |
| SV         | 94.0     | 89.0   | 97.0      | 93.0     |

![OP#1 Training Dataset](image1.png)

Figure 2. OP#1 Training Dataset

### OP#2 Training Dataset

| Classifier | Accuracy | Recall | Precision | F1-Score |
|------------|----------|--------|-----------|----------|
| NB         | 86.9     | 75     | 89.8      | 84.9     |
| LR         | 89.9     | 85     | 96.9      | 93.0     |
| DT         | 91.0     | 85     | 97.0      | 94.0     |
| SV         | 94.0     | 89     | 97.0      | 93.0     |

![OP#2 Training Dataset](image2.png)

Figure 3. OP#2 Training Dataset

### OP#3 Training Dataset

| Classifier | Accuracy | Recall | Precision | F1-Score |
|------------|----------|--------|-----------|----------|
| NB         | 86.9     | 75     | 89.8      | 84.9     |
| LR         | 89.9     | 85     | 96.9      | 93.0     |
| DT         | 91.0     | 85     | 97.0      | 94.0     |
| SV         | 94.0     | 89     | 97.0      | 93.0     |

![OP#3 Training Dataset](image3.png)

Figure 4. OP#3 Training Dataset
7. Conclusion
The algorithm used in large-scale data analyses has had an effect on the digital transition in the 5G era. This paper describes two interdisciplinary methods for converting traditional HetNets to 5G by adding a user-centred machine learning dimension. A BDA-powered platform has been proposed to optimize the allocation of uplink radio resources through HetNets. The aim is to prioritise HetNet stroke emergency patients in order to include the highest possible wireless coverage. Furthermore, resource distribution should be relative to severity of patient's medical condition (i.e., the likelihood of a stroke), as expected by an ensemble method classifying vital sign readings from related and neighbouring IOT sensors. The WSR Max and the PF are two mechanisms, representing the justice function and the average SINR, respectively (both at system and user level). The WSR Max approach increased operator's average SINR up to fifty seven percent, while other method increased the same up to ninety five percent. WSR Max has registered an average SINR of 2163 to 1263 for standard apps, while a stability PF solution has a SINR of 1089 to 1066. To measure consumer fairness, the WSR Max scored from 104 to 156 with SD, while a reliability-conscious PF strategy scored from 44 to 74. Furthermore, the ensemble protocol is tested for improved confidence in the predicted chance of stroke, up to 93 percent accuracy, false positive rate of near about three percent/ false negative rate of eleven percent achieved.

8. Future Scope
The proposed OP-Centric Optimization Framework may play an important role in constructing a scalable, trustworthy and versatile network. Research consisted of three supervised classifications. These classificatory are NB classification, DT classification and LR classification. In future analysis, various classifiers may be used to work on the data set of the OP.

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