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A MULTIFACETED AI-DRIVEN RADIO NETWORK

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ABSTRACT

This paper discusses a unique and revolutionary type of radio network which is driven by various AI techniques. Besides the traditional features of any FM radio network, Radio Logos has incorporated into its system a variety of automated features like weather forecasts, earthquake announcements, monetary exchange rates, listener song requester capability, and the monitoring of equipment. In addition, an advanced real-time defect monitoring system for RF signals has been developed and implemented to monitor the network 24/7. These methodologies are based upon AI techniques ranging from the simple to the advanced.

KEYWORDS

AI, machine learning, FM radio network, RF signals, MPX, RTL-SDR, time-series, big data, pattern recognition, discriminant analysis, analysis of covariance, logistic regression, NLP, real-time monitoring.

1. INTRODUCTION

Radio Logos is the largest regional FM radio network in the European country of Albania. It currently consists of five transmission sites (with two more in the implementation stage) each with its own unique FM frequency (MHz). These sites are interconnected by means of either microwave links or by IP LAN connections. Practically speaking, this setup gives the listener uninterrupted and simultaneous broadcast over a wide geographical area of Albania.

The first goal of Radio Logos is to bring quality music and edifying programs to its listeners. To fulfill this goal, a dedicated staff works tirelessly behind-the-scenes doing traditional studio tasks such as news research, music selection, interviews, recording, editing, and mounting to produce a listener-enjoyable product. Much has been made of recent so-called cost-saving innovations such as Futuri AudioAI (formerly RadioGPT) [1], ChatGPT [2], GPT-4 [3], and speech synthesis technology [4] that can find stories, write scripts, and even host an AI-generated talk show. While these are clever techniques that, in fact, can be implemented, the output of the algorithms could very well be based upon the latest social media trends, the content of which might lack truth and, thus, be in opposition to the moral ethics of the radio station. In addition, AI generated stories and so-called talk shows lack the personal touch of real local people who are in daily contact with the regional audience and know their needs. Thus, it is not unusual that the AI-generated speaker comes across as just that – a fake person. Nevertheless, AI-generated techniques can and should be integrated into any radio network, methodologies that, in fact, reduce operating expenses, ease the burden upon the staff, and create listener-sought programs. Some of these programs will be presented in Section III.

The second goal of Radio Logos is to maintain uninterrupted and quality broadcasting over its entire regional network. During the propagation process of the FM signal, all sorts of defects can happen to distort the final transmission - electrical problems, cable defects, weather-related issues, equipment failures, etc. To maintain a quality FM signal, these defects need to be identified and repaired quickly. If not, our listening audience will seek other sources for their audio enjoyment. Therefore, a highly sophisticated AI-driven real-time defect analysis system has been developed and implemented. This will be discussed in Section IV.

2. HOW DO WE USE THE TERM "AI-GENERATED"?

Before embarking upon a discussion of AI-generated techniques, it is important for the reader to know what we mean by this expression.

First, there are several methods that are cited in contemporary literature that are, in the author's opinion, different words for basically the same thing – newer terms like AI, Machine Learning, Deep Learning and Big Data along with older terms like Pattern Recognition and Discriminant Analysis. Although one might argue that each is a different methodology, they are, in essence, all attempting to solve the same thing – theoretically modeling a real-life problem and then empirically estimating the solution to the equations and/or algorithm.

Second, to further emphasize the above point, whether new or old, all the above techniques involve the use of the same basic tools – computers, algorithms, software, databases, mathematics, and statistics. Therefore, the idea of saying that we have developed an AI-generated technique is somewhat misleading since there is no intelligence being created. Likewise, the expression Machine Learning gives the wrong impression that a machine is somehow learning something. Nothing could be further from the truth. We are simply using computers with mathematical and statistical tools, perhaps in a new and clever manner, to solve equations, algorithms and, ultimately, the problem. Sometimes the solutions are "deep", that is, they are complex equations involving many parameters with interaction terms.

Thirdly, the term "Big Data" is a very "hot" topic, so much so that it is now a required course in many CS programs. Unfortunately, like the topics mentioned above, it is quite misleading. It is often presented in a manner that gives the listener the idea that "Big Data" is an issue that has only arisen in recent years. It must be understood that what is defined today to be "Big Data," will become "Small Data" in a few years. The reality is that, over the years, each generation of scientists has been confronted with analyzing what they considered, at that time, to be a large amount of data. As a result, they had to develop new mathematical, computer, and statistical techniques to solve the problem in question. While it is true that the "Information Age" continues to make available for analysis massive amounts of data, this does not change the basic thrust of ongoing scientific research – not the creation of new intelligence, but the use of computers and mathematical tools to process the data and arrive at solutions. As a final thought, just because one has a problem involving "Big Data," this does not mean that the solution must be "big." On the contrary, a good solution to a problem might be something much simpler than overly complex models involving thousands of parameters. Sometimes, simpler is better.

Finally, Natural Language Processing (NLP) techniques are routinely used in solving many contemporary problems and fall under the umbrella of "computer and mathematical tools."
Therefore, our use of the term "AI-generated" methodologies simply means that we are using mathematical and computer tools to solve our problems. Perhaps we could have chosen as a title "A radio network driven by computer science and mathematical methods." However, it seemed much simpler to use the expression "AI" with the understanding that its meaning is as described in the points above.

3. LISTENER-SOUGHT PROGRAMS

As previously mentioned, radio listeners enjoy hearing regular information programs. Of course, news broadcasts are at the top of the list and are carefully created by our staff. However, there are other programs that are AI-generated such as weather reports, exchange rates announcements, and flash-news involving earthquakes.

3.1. Weather Reports

Using traditional methods, this is a high-cost product since it requires a person to be available at all hours of the day, especially in the early hours of the morning when such information is highly sought. However, using AI techniques, such reports can easily be produced, broadcast at any time of the day, and sound like a live report to the listener.

How is this done? The first step is one labor intensive day for the person who will do the weather reports. In Albanian, the person will read a variety of introductions, city names, temperatures, and weather conditions, and a selection of closing comments. These are then edited, processed using audio tools, and made ready for the next step.

Several minutes prior to the scheduled weather broadcast times, a software program (e.g. written in Python or R) is activated to automatically read weather related webpages, extract (for today and tomorrow) the high and low temperatures and weather conditions (e.g. snow, rain, sunshine, etc.). This is done for a variety of cities that fall in our network coverage. Then another software program will use this information to select the needed audio files from our inventory of pre-recorded information, combine these files in the correct order to produce a broadcast ready weather report. It must be added that the program will randomly select an introduction and closing from the inventory to give the broadcast a non-monotonic sound. In the end, our listeners think that we have a person at the studio 24/7 giving weather reports, so "live" these reports sound.

3.2. Exchange Rates

Perhaps in other countries, such a program would generate little interest. However, a large percentage of Albanians work outside of the country and send money (mainly Euros and USD) back to their loved ones. Thus, people have an interest in the daily exchange rates for these two currencies. The method to produce such programs is identical to the procedure for the weather reports except that the pre-recorded files include decimal numbers not just integers. In the end, it is broadcast twice a day and sounds like a live report.

3.3. Earthquakes

There is nothing more that will generate interest from our listening audience than a good earthquake. How big was it? Where was it located?

First, we read a website that reports Mediterranean area earthquakes in real-time. Second, we narrow the list down to those earthquakes that have occurred within the last two hours, greater than 4.0, and are within a 300 km radius from the studio. The latter step involves the use of a sophisticated trigonometric equation. Third, using a list of major cities that are within the 300 km radius, we find the nearest city to the epicenter. Of course, all possible introductions, cities, and strength must be pre-recorded. Fourth, our software program combines the necessary files to produce a very live-sounding broadcast. Finally, since earthquakes are unpredictable, this newscast falls into the category of "flash-news." That is, whenever it happens, we must be ready to put out a broadcast. This means that our software program is constantly running in the background, monitoring the earthquake webpage, and ready to produce the audio report at a moment's notice.

3.4. User Song Requests

To our knowledge, we are the only Albanian radio station that allows listeners to request songs by means of our website or Android app. The listener requests a specific title or songs by a particular artist, a list of possibilities is returned from our inventory of approximately 5000 songs, the selection is made, and a few minutes later the song is broadcast over the entire network. Truly, our network is listener oriented.

Admittedly, the above AI-generated techniques are simple in that they primarily are using NLP and audio techniques combined with some clever software programming. However, the next section describes a more sophisticated methodology that involves a large quantity of data, mathematics, statistics, and time-series analysis.

4. Real-Time Defect Analysis System

Besides the goal of transmitting quality music and edifying programs, another major goal is to keep the network running smoothly. It is foolhardy to think that one does not need to invest a great deal of time and money into this effort. Undetected defects in the FM broadcast signal will obligate the listeners to turn off their radios or switch to another station.

Radio Logos has multiple antenna sites, each transmitting at a different FM frequency. Of course, a good method to monitor defects is for the operator to simply listen to the radio. However, with a regional radio network, this is impossible since usually only one frequency will be heard in the geographical area of the studio. Traditionally, the method for monitoring a remote site was to ask someone in that area to be your "controller." Unfortunately, not even a faithful controller would be able to listen to the broadcast 24/7. As a result, defects could continue for hours, perhaps days, without being detected. Therefore, a low-cost AI-generated system was needed that would be capable of monitoring the entire network 24/7.

To do this, we installed at every transmission site an internet connection and a RTL-SDR (RealTek Software Defined Radio) dongle attached to a Windows-based computer. The RTL-SDR dongle is an inexpensive device (less than $50) that can be used as a computer-based radio scanner for receiving live radio signals up to 1766MHz which means that it can monitor any FM transmission but also the micro-wave signals of our links that interconnect our transmission sites. GNU radio [5] also has to be installed. Afterwards, using software like Python or R, the device can be activated.

Figure 1. RTL-SDR Dongle [found on RTL-SDR.com]

RTL-SDR devices have been used in a variety of applications. For example, environmental monitoring [6], spectrum monitoring [7,8,9,10], radio coverage maps [11], processing

Electrocardiogram (ECG) signals [12], and remote monitoring of the content of FM broadcasting [13,14].

However, in our situation we will use the device to mathematically “listen” to the FM signal at any time during the day and immediately decide if it was defective or not. However, this required a database of actual transmissions, data from which we could build our corresponding mathematical models to solve this problem.

4.1. Data Collection and the Feature Vector

Using the RTL-SDR device, over the course of five months, we recorded over 2300 10-second FM audio samples. For example, at the FM frequency of 88.6 MHz, the DOS type of command which is passed to the GNU Radio directory was.

rtl_sdr -f 88600000 -g 10 -s 225001 -n 2250010 Capture.dat

These samples (2349) were recorded from our five FM transmission sites. The table below shows the number of samples collected at each site, its frequency (in MHz) and site name. Our policy was to use 80% of our data for training purposes (1879) and 20% for testing (470).

Table 1. Transmission sites and sample sizes

88.6 Gramsh	94.2 Pogradec	96.3 Elbasan	100.3 Librazhd	103.5 Cevernake
447	704	605	351	242

It is imperative to realize that each of the above RTL-SDR generated files is an IQ data file of size 4395KB. From these files, we must extract our multi-dimensional feature vector to be able to analyze the signal for defects. How do we do this?

First, since an FM signal is made up of various components, one of the primary ways to analyze it is to examine, in the frequency domain, its MPX (Stereo Multiplexed signal) spectrum plot. Theoretically, it looks like what is shown in Figure 2 [15]. It is made up of four primary components - the mono, pilot, stereo and RDS (Radio Data System) [16,17,18] components. The mono and stereo parts will move up and down a bit according to the audio that is being transmitted whereas the pilot signal is, theoretically, a constant value and serves, as its name indicates, as a pilot or reference point. The RDS component contains the information that shows up on the radio screen. For example, the name of the radio station, the song title, etc.

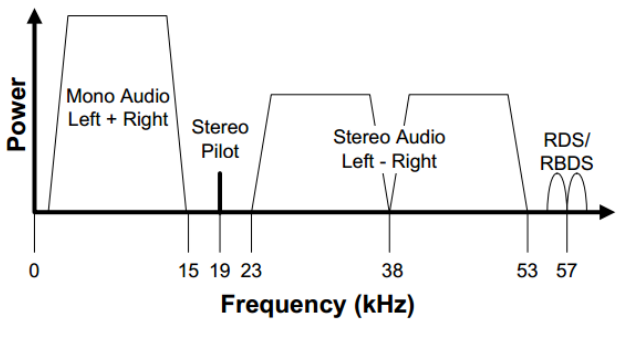

Figure 2. Theoretical MPX spectrum plot

The 10-second sample from the RTL-SDR device will produce a real-time representation of this theoretical plot. Figure 3 shows what it might look like in real-life. We call this the "raw" spectrum plot.

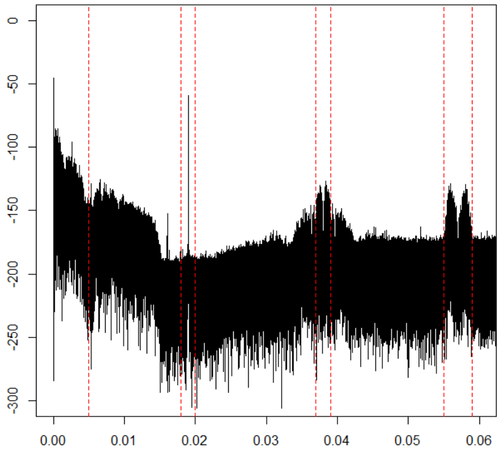

Figure 3. Real-time MPX spectrum plot (x-axis in MHz)

Several potential feature-vector variables can immediately be calculated from this empirical plot, namely, the maximum value of the four primary components of the spectrum plot, their respective powers, their relative powers with respect to the entire spectrum, and their relative powers with respect to the total power in the rds spectrum interval. For example, the variable "pilot" is the maximum value of the spectrum plot in the interval (0.018,0.20). Pilot_power is the sum of the power in that interval, pilot_power0 is its percentage of the total power, and pilot_power1 is the ratio of pilot_power and rds_power. Likewise, similar variables are calculated for DB, stereo and rds using the vertical dashed line intervals in Figure 4. See also Table 2.

Table 2. Spectrum plot feature vector variables

From IQ data	DB	pilot	stereo	rds
From wave file	DB0	pilot0	stereo0	rds0
Freq intervals	(0,.05)	(.018,.020)	(.037,.039)	(.055,.059)

Likewise, using the IQ data file, a wave file of the 10-second audio clip was reconstructed by means of some complex mathematics. After normalizing this wave file, we reversed the mathematics and, once again, created a modified MPX spectrum plot where we extracted the modified variables DB0, pilot0, stereo0 and rds0.

Many other potential feature vector variables describing the audio signal were extracted from each wave file, some (but not all) of which are listed below.

Table 3. Additional feature vector variables

H	Total entropy of a time wave.,
M	Acoustic index based on the median of the amplitude envelope.,
ac	Acoustic complexity
ad	Acoustic Diversity
ae	Acoustic evenness
rms	The root mean square.
crest1	The crest factor of an audio signal
zcr	The zero-crossing rate
Z90AB	The number of times the station code for Radio Logos (90AB) is found in the RDS part of the signal.

The Mel-Frequency Cepstral Coefficients (MFCC) are often used in speech recognition [19], even in identifying illegal broadcast stations [20]. In our situation for identifying defective signals we used the wave file and extracted 12 MFCC which is a 998x12 matrix. For each of the 12 columns, we calculated five statistics – the mean, the variance, the skewness, the kurtosis, and after discretizing the vector of values into bins, the information entropy. For example, from the 1st MFC coefficient we extracted MC1, MC2, MC3, MC4 and MC5 which represent the above five statistics. In the end, we had a vector of length 60.

These site/time variables were also added to the feature vector and after adding the interaction term for Hour by Minute, the dimension of our final feature vector was over 150.

Table 4. Site/Time feature vector variables

Site	The transmission site
Weekday	Which day of the week.
Hour	Which hour of the day
Minute (0 or 1)	0=1st half or hour, 1=2nd half.

The last step of our data preparation was to determine the defect status for every wave file. While the norm would be to decide if the audio was either good or bad [21], we expanded the output dimension to three. That is, the author of this paper listened carefully to every audio file and decided if it was good (OK), bad (DF), or very bad (VB). The guideline that was followed was that the audio would be labeled good if it sounded normal and bad if it contained some background noise, a random pop noise or a minor distortion, something that a listener may or may not notice. The audio was labeled very bad if it contained excess static beyond a background noise, abnormal silence, major distortion, or was completely missing.

Although the problem is multi-nominal since we have three outcomes (OK, DF, VB), we divided the problem into three binomial comparisons, namely, OK versus DF, DF versus VB, and OK versus VB and used the majority opinion method to predict the status of the audio file.

To do this, we followed an ancient saying which says, “In the mouth of two or three witnesses shall every matter be established.” We applied this good advice by constructing two different statistical models (a logistic regression model and a decision tree) for each of the above three comparisons. For the logistic models we used a variety of proven statistical procedures (e.g. sequential and partial p-values, R^2, AIC, multicollinearity, error rates of the confusion matrix, stepwise constructions, etc) to determine the “best” equations with the fewest feature vector variables. problem. The author did experiment with other more complex statistical methods (e.g. Neural Networks), but their analyses did not yield any significant improvements. Thus, the simpler techniques (logistic regressions and decision trees) were chosen.

4.2. Comparison 1: OK versus DF

For this comparison we forced our logistic regression models to first include the “site/time” variables. Thereafter, we investigated the inclusion of other feature vector variables. The reason for this is that not every transmission site nor transmission times are the same. Some sites have more natural background noise than others due to the close proximity of other RF (Radio Frequency) transmission sources which affect the RTL-SDR device. Likewise, some days of the week and some hours of the day have more talk shows which increases the likelihood of background noise being heard.

The training sample breakdown for this comparison was 1029 good and 727 bad audio files. The best logistic regression model for this comparison is below. Since we are comparing OK with DF, we are calculating the probability of the audio being bad (DF) versus good (OK). The syntax we use is L12 to indicate that this is the logistic probability model for groups 1 and 2. A similar syntax is used for the other models.

$$P_{L12}(DF) = \frac{1}{1 + \exp(-eq)}, where$$

$$eq = 7.55 + \begin{cases} 0, if\ Friday \\ 0.5, if\ Monday \\ 0.7, if\ Saturday \\ 0.1, if\ Sunday \\ 0.3, if\ Thursday \\ 0.3, if\ Tuesday \\ -0.1, if\ Wednesday \end{cases}$$

$$+ \begin{cases} 0\ if\ Hour = 0 \\ 3.6\ if\ Hour = 1 \\ 3.3\ if\ Hour = 2 \\ \dots \\ 3.3\ if\ Hour = 18 \\ \dots \\ -12.9\ if\ Hour = 23 \end{cases} + \begin{cases} 0, if\ Minute = 0 \\ 0.6, if\ Minute = 1 \end{cases}$$

$$+ \begin{cases} 0, if\ Site = Gramsh \\ -0.7, if\ Site = Cevernake \\ -1.6, if\ Site = Gramsh \\ 0.3, if\ Site = Pogradec \\ -0.6, if\ Site = Elbasan \end{cases}$$

$$+ \begin{cases} 0 \quad all\ other\ combinations \\ -1.2\ if\ Hour = 1\ and\ Minute = 1 \\ 0\ if\ Hour = 2, andMinute = 1 \\ \dots \\ -3.6\ if\ Hour = 18\ and\ Minute = 1 \\ \dots \\ 0.6\ if\ Hour = 23\ and\ Minute = 1 \end{cases}$$

$$-0.56 * MC6 - 0.18 * MC1 - 1.70 * MC3 - 0.16 * pilot$$

Obviously,

$$P_{L12}(OK) = 1 - P_{L12}(DF)$$

The ANOVA table reveals that, in fact, all the site/time variables are very significant and should be included in the model. For example, ignoring the intercept, Weekday and Site factors, when Hour =18 and Minute =0 the coefficients add up to 3.3+0+0=3.3, whereas for Hour=18 and Minute =1, the coefficients add up to 3.3+0.6-3.6=0.3. This means that the probability of a bad audio is lower for the second half of Hour 18. Many other hours had similar results. The reason for this is that we tend to broadcast our talk shows during the first half of every hour. The other significant feature vector variables are MC6, MC1, MC3 and pilot. For example, according to the model, when MC6 increases the probability of DF decreases.

Table 5. ANOVA table for OK vs DF

Source	**Df**	**SS**	**MS**	**F**	**Pr(>F)**
Weekday	6	27.38	4.56	58.1	0
Hour	23	71.70	3.12	39.7	0
Minute	1	48.93	48.93	622.7	0
Site	4	3.26	0.82	10.38	0
HourxMinute	23	50.19	2.18	27.3	0
MC6	1	80.61	80.61	1026	0
MC1	1	6.64	6.64	84.6	0
MC3	1	3.89	3.89	49.5	0
pilot	1	0.34	0.34	4.34	0.04
Residuals	1694	133.07	0.08		

Although we attempted to allow the site/time variables to be included, the decision tree algorithm chose only MC2, MC6, and MC7 to form the tree (see Table 6).

Table 6. Decision Tree for OK vs DF

Node	**Variable**	**Probability**	**Cut-off value**
1	MC2		<72.0773
2	MC6		<-1.41261
4	<leaf>	0.73770	
5	<leaf>	0.04995	
3	MC6		<-1.50283
6	<leaf>	0.97210	
7	MC7		<40.5805
14	<leaf>	0.3590	
15	<leaf>	0.75860	

For example, if MC2=79, MC6=-1.0 and MC7=40, the tree returns 0.35900 which means that we would say that the signal is good (OK). The above probabilities will be labeled as PT_{12}(DF). In addition, the error rates from the 2x2 confusion matrices of these two models were in the 7.5% range. This is not surprising since at times it is difficult to discern if the audio is good or bad.

4.3. Comparison 2: DF versus VB

The training sample breakdown for this comparison was 727 bad and 123 very bad audio files. However, variable Hour and the interaction term HourxMinutes could not be used due to insufficient data. Nevertheless, the best logistic regression model for this comparison is below. The ANOVA table reveals that, although the variables Weekday, Minute and Site are almost all significant, the most influential variable (high SS value) in the entire model is rds_adj which is the ratio of rds and zcr. The reason for the site/time variables having a smaller impact than the

OK vs DF model is that VB defects occur randomly, whereas DF defects tend to show up (although not exclusively) during the first half of the hour.

Table 7. ANOVA table for DF vs VB

Source	**df**	**SS**	**MS**	**F**	**Pr(>F)**
Monday	1	0.26	0.26	8.059	0.004
Saturday	1	0.47	0.47	14.406	0.000
Sunday	1	0.05	0.05	1.614	0.204
Thursday	1	0.48	0.48	14.769	0.000
Tuesday	1	0.39	0.39	12.033	0.000
Wednesday	1	0.01	0.01	0.417	0.518
minute0	1	3.98	3.98	123.360	0
site103_5	1	0.00	0.00	0.011	0.915
site88_6	1	1.86	1.86	57.588	0
site94_2	1	0.74	0.74	23.053	0
site96_3	1	2.37	2.37	73.357	0
rds_adj	1	58.08	58.08	1798.561	0
stereo_power0	1	3.46	3.46	107.134	0
MC5	1	6.08	6.08	188.250	0
Residuals	835	26.97	0.03		

The logistic regression formula is shown below.

$$P_{L23}(VB) = \frac{1}{1+\exp(-eq)}, where$$

$$eq = 67.76 + \begin{cases} 0, if\ Friday \\ 3.3, if\ Monday \\ 0.5, if\ Saturday \\ -2.2, if\ Sunday \\ -2.5, if\ Thursday \\ -1.4, if\ Tuesday \\ -2.9, if\ Wednesday \end{cases}$$

$$+\begin{cases} 0, if\ Minute = 0 \\ 4.0, if\ Minute = 1 \end{cases}$$

$$+\begin{cases} 0, if\ Site = Gramsh \\ -10.0, if\ Site = Cevernake \\ -3.3, if\ Site = Gramsh \\ -6.3, if\ Site = Pogradec \\ -1.6, if\ Site = Elbasan \end{cases}$$

$$+\ 0.1 * rds\_adj - 238.7 * stereo\_power0 - 16.3 * MC5$$

Obviously,

$$P_{L23}(DF) = 1 - P_{L23}(VB)$$

The decision tree algorithm chose rds0_adj (rds0/zcr), MC5 and MC16. The details are below.

Table 8. Decision Tree results for DF vs VB

Node	Variable	Probability	Cut-off value
1	rds0_adj		<-240.195
2	MC5		<1.68935
4	<leaf>	0.72723	
5	<leaf>	0.00694	
3	MC16		<25.3674
6	<leaf>	0.99090	
7	<leaf>	0.11111	

The above probabilities will be labeled as $PT_{23}(VB)$. In addition, the error rates from the 2x2 confusion matrices of these two models were in the 1% range. In other words, their discriminating power is high.

4.4. Comparison 3: OK versus VB

The training sample breakdown for this comparison was 1029 good and 123 very bad audio files. Like the previous category, the variable Hour and the interaction term HourxMinutes could not be used. The ANOVA table reveals that the most influential variable in the entire model rds0_adj which is the ratio of rds0 and zcr.

Table 9. ANOVA table for OK vs VB

Source	df	SS	MS	F	Pr(>F)
Monday	1	0.41	0.41	12.43	0
Saturday	1	4.72	4.72	141.9	0
Sunday	1	2.38	2.38	71.44	0
Thursday	1	0.20	0.20	5.91	0.015
Tuesday	1	0.36	0.36	10.70	0.001
Wednesday	1	0.09	0.09	2.84	0.09
minute0	1	0.91	0.91	27.4	0
site103_5	1	0.05	0.05	1.47	0
site88_6	1	0.96	0.96	28.8	0.915
site94_2	1	0.00	0.00	0.01	0
site96_3	1	0.75	0.75	22.4	0
rds0_adj	1	34.91	34.91	1048.8	0
stereo_power0	1	13.68	13.68	411.1	0
MC5	1	12.51	12.51	375.8	0
crest1	1	0.13	0.13	4.0	0.047
Residuals	1136	37.81	0.03		

The best logistic regression model is shown below.

$$P_{L13}(VB) = \frac{1}{1+\exp\left(-eq\right)}, where$$

$$eq = 2771.7 + \begin{cases} 0, if\ Friday \\ 180.9, if\ Monday \\ 214.7, if\ Saturday \\ -56.3, if\ Sunday \\ -308.6, if\ Thursday \\ -48.5, if\ Tuesday \\ -233.0, if\ Wednesday \end{cases} +$$

$$+ \begin{cases} 0, if\ Minute = 0 \\ 425.2, if\ Minute = 1 \end{cases} + \begin{cases} 0, if\ Site = Gramsh \\ -50.5, if\ Site = Cevernake \\ -30.7, if\ Site = Gramsh \\ -47.3, if\ Site = Pogradec \\ -54.9, if\ Site = Elbasan \end{cases}$$

$$+3.5 * rds0_{adj} - 16609.7 * stereo_{power0} - 1134.3 * MC5 + 1003.4 * crest1$$

Obviously,

$$P_{L13}(OK) = 1 - P_{L13}(VB)$$

The decision tree algorithm chose rds0_adj, pilot, MC5 and stereo_power0. The details are below.

Table 10. Decision Tree results for OK vs VB

Node	Variable	Probability	Cut-off
1	rds0_adj		<-239.107
2	MC5		<1.54551
4	pilot		<-46.0433
8	<leaf>	1.0	
9	<leaf>	0.20	
5	<leaf>	0.0058	
3	stereo_power0		<0.0767323
6	<leaf>	1.0	
7	<leaf>	0.40	

The above probabilities will be labeled as P_{T13}(DF). In addition, the error rates from the 2x2 confusion matrices of these two models were in the 1% range. In other words, their discriminating power is high.

4.5. The Majority Opinion Algorithm

As previously mentioned, we will use the majority opinion method to determine if an audio file is good, bad, or very bad. That is, for a given audio file we calculate the following probabilities using the above six formulas. For example, for audio file 1, we have P_{L12}=.94 which means we would choose DF, for P_{L23}=0, we would choose DF, and so on. For audio file 2, we have P_{T12}=.76 which means we would choose DF, for P_{T13}=0.01, we would choose OK. The column labeled “Final Choice” is the majority opinion.

Table 11. Majority Opinion Example

File	P_{L12}	P_{L23}	P_{L13}	P_{T12}	P_{T23}	P_{T13}	**Final Choice**
1	0.94	0.00	1	0.97	0.01	0.01	
Choice	DF	DF	VB	DF	DF	OK	DF
2	0.93	0.79	1	0.76	0.01	0.01	
Choice	DF	VB	VB	DF	DF	OK	DF

Using this procedure on the test data, the results show that there are only 2 concerning errors. The other errors simply reflect the difficulty of discerning between a good and bad audio file as the differences might be very minor background noise, a "pop", or something else that is of little importance. Serious errors would be to say that the audio file is good when, in fact, it is very bad. Or, to say it is very bad when it is good. Fortunately, we have no such errors which indicates that these six formulas have high discrimination power.

Table 12. Majority Opinion for the test data

Actual/Predicted	**OK**	**DF**	**VB**
OK	229	23	0
DF	19	166	0
VB	0	2	31

Investigating these two audio files we find that the first file had a slight excess silence at the beginning of the file, but the rest of the file was of excellent quality. In fact, this file could have been classified as bad instead of very bad. The second file had some static during the last 3 seconds, so really was a very bad file. All-in-all, our data analysis shows that our AI-based algorithm is very effective for the real-time monitoring of our radio network signals.

4.6. Implementation

The practical implementation of this algorithm consisted of several steps. First, this algorithm was invoked several times per hour. Secondly, if the algorithm said that the file is good, then no action was taken. If results indicated that the audio is very bad, then the results were immediately relayed back to the studio (via the internet) for further investigation. If the algorithm said that audio is bad, then usually it is a momentary and isolated event. However, if this "DF" status continued to appear with several sequential observations, then it was an early warning sign that the signal is degrading and heading in the direction of VB. Such a situation would be communicated to the studio and warrant further investigation.

5. CONCLUSIONS

While AI technology is sometimes clouded in mystery and awe, our hope is that the reader will have obtained a better understanding and appreciation of this field after studying the details of our multifaceted AI-driven radio network. Some AI techniques can be very simple and involve only basic computer science and NLP operations while others are more complex. As our analysis demonstrated, AI techniques do not necessarily have to involve formulae of thousands of parameters. Sometimes the AI solution can be simple, yet effective, as was demonstrated by our application where the dimension of our most complicated formula was less than 60.

Finally, our hope is that this article will encourage other radio networks to develop and implement such AI methodologies.

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