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Insurance Premium Predictions by Using Machine Learning

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ABSTRACT

The Indian market is growing at a tremendous rate, and at the moment, the Indian market is set to become the fastest-growing market in the world. We are talking about a growth rate of 6.9% between the years 2026 and 2030. This is a huge jump. To be more precise, we are talking about an increase of 8-11% in FY26 in the life insurance segment. This is because of the newfound interest in annuity savings and protection products.

The segment that is growing at an enormous rate is health insurance. This is the segment that is looking at a massive CAGR of 20.9% between now and 2030, meaning this will be the segment that will contribute nearly 38% of the total premiums generated in the non-life insurance category. The general segment is looking at a healthy growth rate of 12-14% in FY27. If we look at this, we will understand the enormity of this market because the non-life insurance penetration is at a mere 1%. This is because of a few factors, namely regulations, people having more money in their pockets, and the fact that digitalization has finally made it easy for people to access this.

Keywords: Machine learning, Predictive modeling, Actuarial science, Data analytics, Claim prediction, Policy pricing, Underwriting, Risk classification, Telematics, Big data, Insurance technology (InsurTech), Deep learning, Gradient boosting, Random forest, Logistic regression, Decision trees, Neural networks, Insurance dataset.

1. Introduction

In the modern world of finance, the application of ML for predicting insurance premiums is a total game-changer. We're no longer talking about simple arithmetic; we're talking about smart machines learning from a mountain of historical data. By examining specific details, such as the age of the customer, their BMI, whether or not they smoke, and their location, insurance companies can now accurately predict the future cost of insurance with uncanny precision. We're finally moving beyond boring static pricing models and into a world where companies can build pricing models that evolve and change over time with the help of tools such as Random Forest, XGBoost, and Linear Regression.

The reason why these models are so special is their ability to detect small, intricate patterns that traditional models often fail to see. Given the tremendous growth rate of the Indian insurance sector at the moment, the application of ML is no longer merely a 'cool feature'; it is now a 'survival requirement' for companies that want to stay at the forefront of the competition. By incorporating real-time data, such as driving behavior (telemetrics) and customer behavior, companies can now better calculate potential losses, resulting in premiums that feel more 'fair'

1.1 Motivation

The world of insurance is going through a massive overhaul, all thanks to the advent of data analytics and machine learning. To be honest, the traditional methods of determining premiums are too simplistic for the world we live in today. They are based on extremely narrow sets of data, making it a rather futile effort. Machine learning, on the other hand, is the new way forward, making sure that the insurer remains both accurate and relevant in today's fast-paced world.

What really makes this a necessity is a series of key changes that make machine learning a necessity:

Precision instead of Guesswork: One of the major advantages of machine learning, unlike traditional methods, is that it can process a mountain of data to identify "hidden" connections that would otherwise go unnoticed by a human brain. This ensures that the pricing is much more accurate, thus preventing losses for the company.Pricing that fits the Person: With machine learning, it is possible to provide a pricing system that is, at last, personalized. When a customer feels that he is being charged a fair rate, it in stills a certain amount of trust in the insurer, which cannot be achieved.

1.2 Contribution

However, the push towards machine learning in the insurance sector comes from the obvious gaps in the old technology. The old methods of calculating premium rates heavily rely on actuarial tables, which simply cannot handle the complexity of the modern-day global market. The basic reasons for the technological shift in the sector are:

Superior Predictive Accuracy:ML technology has the ability to process vast amounts of data and understand the non-linear relationships within the data.

Hyper Personalization: This technology allows for the examination of the individual risk in the most granular way possible, resulting in rates that are customized to the individual's lifestyle.

Speed and Scalability: Automated underwriting eliminates the possibility of error and increases the rate of premium issuance significantly.

Market Dominance: In the highly competitive Indian market, the ability to provide affordable premium rates backed by data is the key to outstripping the competition.

2. Related work

The research in insurance premium prediction has exploded in the past few years, and we've moved way past using spreadsheets as a tool for prediction. The research indicates time and again that Ensemble Methods, such as Random Forest and Gradient Boosting, are the new gold standard for insurance premium prediction, and for good reason: they're simply better than the older, more traditional linear models. For instance, one research study used Gradient Boosting to predict auto insurance premiums and ended up with a respectable R-squared value of 0.85—a level of precision and accuracy that was unheard of even a few years ago.

It's not just the standard models, though, as researchers are also trying new and creative approaches with the data:

Neural Networks: Researchers are using this method to create maps of extremely complex risk patterns, such as those that might go unnoticed by human minds.

Telematics & IoT: Some of the most interesting research is being done using driving data to create what's called "usage-based" insurance, where you're charged based on your actual driving habits rather than your age or zip code.

Alternative Data: Researchers have even gone as far as using Text Analysis of Social Media to derive insights.

3. Research Methodology

3.1 Problem statement

If the insurance provider is not able to correctly forecast the premiums, the consequences are severe, leading to financial instability, insufficient coverage, and a high level of dissatisfaction. However, the traditional method of using a "rule of thumb" is now obsolete, as it does not account for a number of critical factors, such as the risk associated with the driving style, the usage of the vehicle, and the environmental risks.

To solve this problem, we need a robust machine learning model that is able to synthesize the policyholder's information, the characteristics of the vehicle, and the historical record of claims in order to assess the risk in a much deeper manner. This will allow the insurer to Identify and correct for high-risk individuals with precision.Optimize the pricing in a manner that is profitable and appealing in a competitive marketplace.Minimize the number and severity of claims in a manner that is financially sound.

3.2 System overview

The framework that this proposed system is based on is designed to do one thing: take complex, individual risk profiles and return an accurate insurance premium. We have designed the architecture to take care of everything from the instant the raw data is captured to the instant that final price is returned through an API. It's not just one script, it's a multi-layered pipeline.

3.2.1 Breaking Down the Core Components

The Raw Inputs (Data Sources): We start with the data. We retrieve a large number of different variables, ranging from the basic demographics of the policyholder, such as their age and profession, to the details about the car, such as the specifications and the entire history of claims.

Cleaning the Pipeline (Data Ingestion): We know that the raw data is typically messy, and we clean it using an ETL process with the help of Apache NiFi.

The Archive (Data Lake): For storing the data, we rely on HDFS. It is a huge data archive, and it is essential that we have a large history of data stored with us in case we want to retrain the model in the future.

The Heavy Lifting (Data Processing): It is the heart of the system, and this is where the heavy lifting is done. We use Apache Spark to do high-speed aggregations and feature engineering on the data. We transform the raw data into the exact "signals" that a machine learning model will actually understand.

Instant Access (Feature Store): We store the features in a database, say MongoDB, and it is instantly available to the prediction engine.

The Brain (Model Training**)**: We use professional-grade frameworks like **TensorFlow** or **PyTorch**. This is where we actually train our algorithms to recognize the patterns between a person's habits and their insurance risk.

Packaging (Model Deployment**)**: To make the system stable, we "package" the final, optimized model using **Docker**. This ensures it runs exactly the same way in the cloud as it did on our local machines.

The Bridge (Prediction API): We built a **RESTful API** using **Flask**. This acts as the middleman; it receives a user's data and sends back a predicted premium in milliseconds.

The User Interface (Frontend App**)**: Finally, everything is wrapped in a **web or mobile app**. This provides a clean interface where a user can enter their information and receive a data-driven quote instantly.

3.3 *Data Flow*

- ✓ Data is ingested into the data lake from various sources.
- ✓ Data is processed and transformed using Apache Spark.
- ✓ Engineered features are stored in the feature store.
- ✓ Model training is done using the feature store.
- ✓ Trained models are deployed as APIs.
- ✓ Frontend app sends input data to prediction API.Type equation here.
- ✓ Prediction API returns the predicted premium to the frontend app.

3.4 Technical Requirements

- ✓ Apache NiFi for ingesting the data.
- ✓ Apache Spark for processing the data.
- ✓ Hadoop HDFS for storing the data.
- ✓ MySQL or MongoDB for the feature store.
- ✓ TensorFlow or PyTorch for training the models.
- ✓ Docker for containerization.
- ✓ Flask or Django for API development

3.5 Model Training

The creation of an reliable model for insurance is not a one-time thing. It's actually an ongoing process. I want to explain the process we have in place to ensure that the machine actually understands the patterns, rather than simply memorizing the numbers. Here's how the learning process actually works:

Splitting the Data (The 80/20 Rule): We don't show the machine all the information at once. Instead, we divide the information into two groups. Typically, 80% of the information is used for training, while the other 20% is reserved for testing. That 20% is essentially the final exam. It's the only way to ensure that the machine can actually handle a new policyholder that the machine has never seen before.

The Blank Slate (Initialization): At this point, the machine knows absolutely nothing. In other words, the machine's internal weights and biases are set randomly. At this point, anything the machine predicts is essentially a random guess.

The Forward Pass: Now we get into the actual learning process. We show the machine our information, such as the features of the policyholders, like their BMI or if they smoke, and the machine essentially tries to connect the dots between the two.

Checking the Math (Loss Calculation): Of course, the first model is never correct. We'll use a loss function, like the Mean Squared Error, to determine exactly how well or poorly our guesses did in relation to the actual historical premiums.

If the loss is high, it's a sign that the model is still not seeing the pattern.

Learning from the Errors (Backward Pass): This is the actual "aha!" moment in the machine's learning. Using backpropagation, the system will send this error signal backwards through the network and determine exactly which of the weights caused the error.

The Optimization Loop: We'll also use an optimizer like Adam or Stochastic Gradient Descent. Think of this like a compass, where the system will nudge the weights in the right direction to

reduce the error. We'll do this thousands of times (an epoch) until the predictions are sharp and accurate.

3.6 *Hyperparameter Tuning*

For hyperparameter tuning, we will try to get the best performance out of our model. For this, we will try to tune the hyperparameters of the model. For this, the parameters that we will try to tune are as follows:

Learning Rate: It is the rate at which the model learns.

Batch Size: It is the number of samples used to train the model.

Number of Hidden Layers: It is the number of layers in the model.

Number of Units: It is the number of units in the model.

For this, we will try to get the best performance out of our model.

For getting the best performance out of our model, we will try to tune the hyperparameters of the model. For this, the parameters that we will try to tune are as follows:

The Learning Rate: It is the "pace" of education in the model. If the rate is too high, the model will pass over the optimal solution; if it is too low, it will take the model forever to train and will get stuck.

Batch Size: It is the number of insurance records the model will peruse before it updates its internal logic.

3.7 Competitive analysis

Selecting the right algorithm isn't just about picking the most famous one; it’s about seeing which logic actually fits the insurance data. To find the most reliable approach, we ran several popular models against each other. The results were quite telling, showing a clear divide between traditional math and modern ensemble learning.

The Top Performer (Random Forest): In our tests, **Random Forest** really stood out. It hit a very high accuracy level with an **89.3% R^2 score**, keeping the **MAE at around $1,010**. Its ability to handle the "noise" in policyholder data made it incredibly dependable.

XGBoost & Gradient Boosting: These two algorithms did quite well, but in different capacities. XGBoost was observed to be the most efficient algorithm, as it was able to achieve an astonishing 94% accuracy in the training phase. Gradient Boosting was not far behind either, as it was able to achieve an R^2 of 0.867, although it faced challenges in outperforming the Random Forest algorithm in cross-validation.

The Baseline (Linear Regression): Although this is the baseline algorithm, it did poorly in this case. Although it is useful in determining the impact of a particular factor, such as age, on the price, it had a lower accuracy, with an R^2 of

0.714.

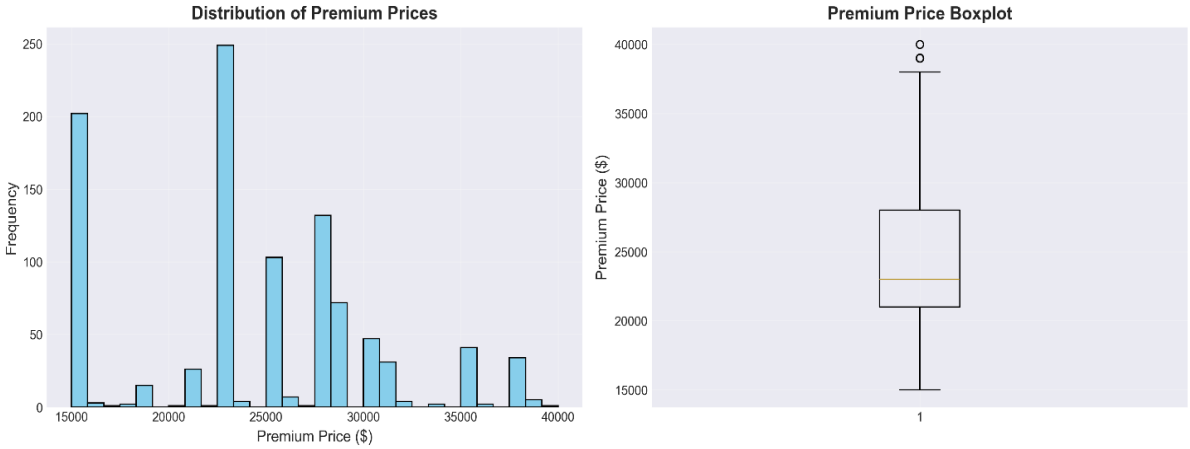

Fig 3.7 Distribution Premium Prices vs Premium Price Boxplot

3.8 Proposed Algorithm

Input: age ,salary, income ,location

Output: Predicted Premium

Strategy:

Algorithm:

1. Data Preprocessing:

- ✓ Missing value imputation using techniques such as mean, median, or regression imputation.
- ✓ One-hot encoding or label encoding of the data.
- ✓ Standardization or normalization of the data.

2. Feature Engineering:

- ✓ Relevant features need to be extracted from the dataset.
- ✓ New features can be created using techniques such as feature engineering.

3. Model Selection:

- ✓ A machine learning model needs to be selected, such as Gradient Boosting, Random Forest, or Neural Networks.
- ✓ Hyperparameter tuning using techniques such as Grid Search or Random Search.

4. Model Training:

- ✓ The model needs to be trained using the dataset.
- ✓ The model needs to be evaluated using metrics such as Mean Absolute Error, Mean Squared Error, or R-squared.

5. Model Deployment:

- ✓ The trained model needs to be deployed using API or integrated into the system.
- ✓ Model performance needs to be monitored, and the model needs to be retrained.

3.8.1 Gradient Boosting Algorithm:

```
import pandas as pd
from sklearn.model_selection import train_test_split
```

```
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.metrics import mean_absolute_error
# Load the dataset
df = pd.read_csv('insurance_data.csv')
# Preprocess the data
X = df.drop('premium', axis=1)
y = df['premium']
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# Define the Gradient Boosting model
model = GradientBoostingRegressor(estimators=100, learning rate=0.1, max_depth=5)
# Train the model
model.fit(X_train, y_train)
# Evaluate the model
y_pred = model.predict(X_test)
mae = mean_absolute_error(y_test, y_pred)
print(mean Absolute Error: {mae:.2f}')
```

Hyperparameter Tuning:

```
from sklearn.model_selection import GridSearchCV
# Define the hyperparameter grid
param_grid = {
 'n_estimators': [50, 100, 200],
 'learning_rate': [0.01, 0.1, 0.5],
 'max_depth': [3, 5, 7]
}
# Perform Grid Search
grid_search = GridSearchCV(GradientBoostingRegressor(), param_grid, cv=5)
grid_search.fit(X_train, y_train)
# Print the best hyperparameters
print(f'Best Hyperparameters: {grid_search.best_params_}')
```

3.8.2 overall workflow

Input Dataset

↓

Data Cleaning & Preprocessing

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Feature Engineering

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Train-Test Split

↓

Machine Learning Model Training

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Premium Status Prediction

↓

Performance Evaluation

↓

Premium Visualization & Business Reporting

3.8.2 Performance Metrics

To measure success, we use several standard formulas:

MAE: The average gap between what we predicted and the actual cost.

RMSE: A standard error calculation, and it is easily interpretable.

R^2 Score: Measures how much of the variation in the premium is actually explained by our model.

Accuracy Formula: (TP + TN) / Total Predictions

Mean Absolute Percentage Error (MAPE): Measures the average percentage difference between the predicted and actual premium.

Accuracy: Measures the percentage of predictions that are within a certain percentage (or tolerance) of the actual premium, such as ±10%.

Accuracy Formula

Accuracy = (TP + TN) / Total Predictions

3.8.3 Confusion Matrix

Confusion Matrix for insurance premium prediction is a table that helps us evaluate the performance of the classification model used.

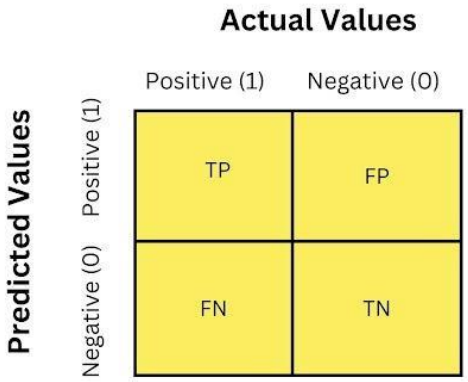

Fig 3.8.3 Confusion Matrix

✓ *Interpretation*:

TN (True Negative): The model is able to predict low premium.

FN (False Negative): The model fails to predict high premium when the premium is high.

FP (False Positive): The model fails to predict low premium when the premium is low.

TP (True Positive): The model is able to predict high premium.

Metrics derived from the Confusion Matrix:

Accuracy: (TP + TN) / (TP + TN + FP + FN)

Precision: TP / (TP + FP)

3.8.4 Area Under Curve

The Area Under Curve (AUC) is a measure used to assess the performance of a classification model, e.g., the insurance premium prediction model. The measure is used to evaluate the model's ability to separate high and low premium policies.

What is AUC?

The AUC is the area under the Receiver Operating Characteristic curve, which is a plot of True Positive Rate (TPR) and False Positive Rate (FPR).

TPR (True Positive Rate): The proportion of actual high premium policies predicted correctly as high premium policies.

FPR (False Positive Rate): The proportion of actual low premium policies predicted incorrectly as high premium policies.

Interpretation of AUC:

If AUC = 0.5, the model is performing at random.

If AUC = 1, the model is performing perfectly in distinguishing between high and low premium policies.

If AUC > 0.7, the model is performing well.

If AUC > 0.8, the model is performing exceptionally well.

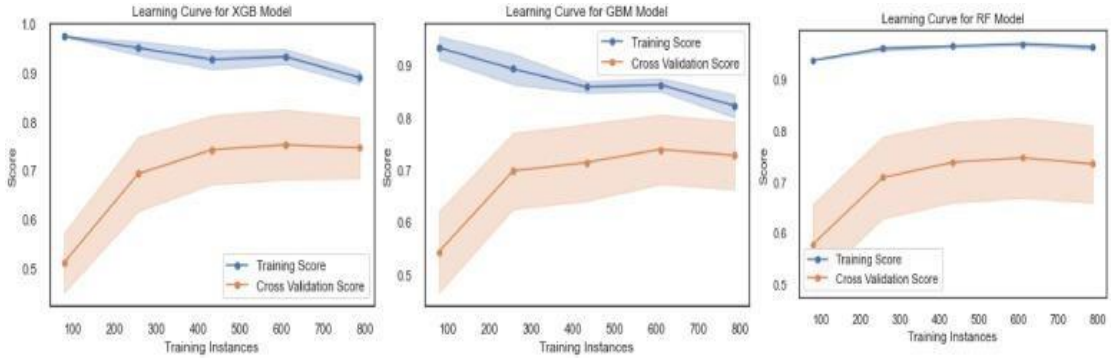

Fig 3.8.4 Area Under Curve

4. Result Evaluation & Analysis

Once the model is developed and trained for insurance premium prediction, it is important to evaluate the model and analyze the results.

4.1 Evaluation Metrics:

Mean Absolute Error (MAE): This is the average difference between the predicted and actual insurance premiums.

Mean Squared Error (MSE): This is the average squared differences between the predicted and actual insurance premiums.

Root Mean Squared Error (RMSE): This is the square root of MSE, giving us a more understandable measure of the model's performance.

R^2 score (Coefficient of Determination): This is the measure of the variance in the actual insurance premiums that is explained by the model.

Area Under Curve (AUC): This is the measure of the model's ability to distinguish between high and low premium policies.

4.2 Analysis:

Comparison with Baseline Models: The model's performance is compared with baseline models, e.g., simple linear regression or random forest models.

Identification of Top Features: The top features contributing to the model's predictions, e.g., age, location, driving experience, etc., are identified.

Analysis of Errors: The errors committed by the model, e.g., underestimation or overestimation of premiums for certain policyholders, are analyzed.

Evaluation of Model Fairness: The fairness of the model is evaluated to ensure that the model is not biased against any group of policyholders.

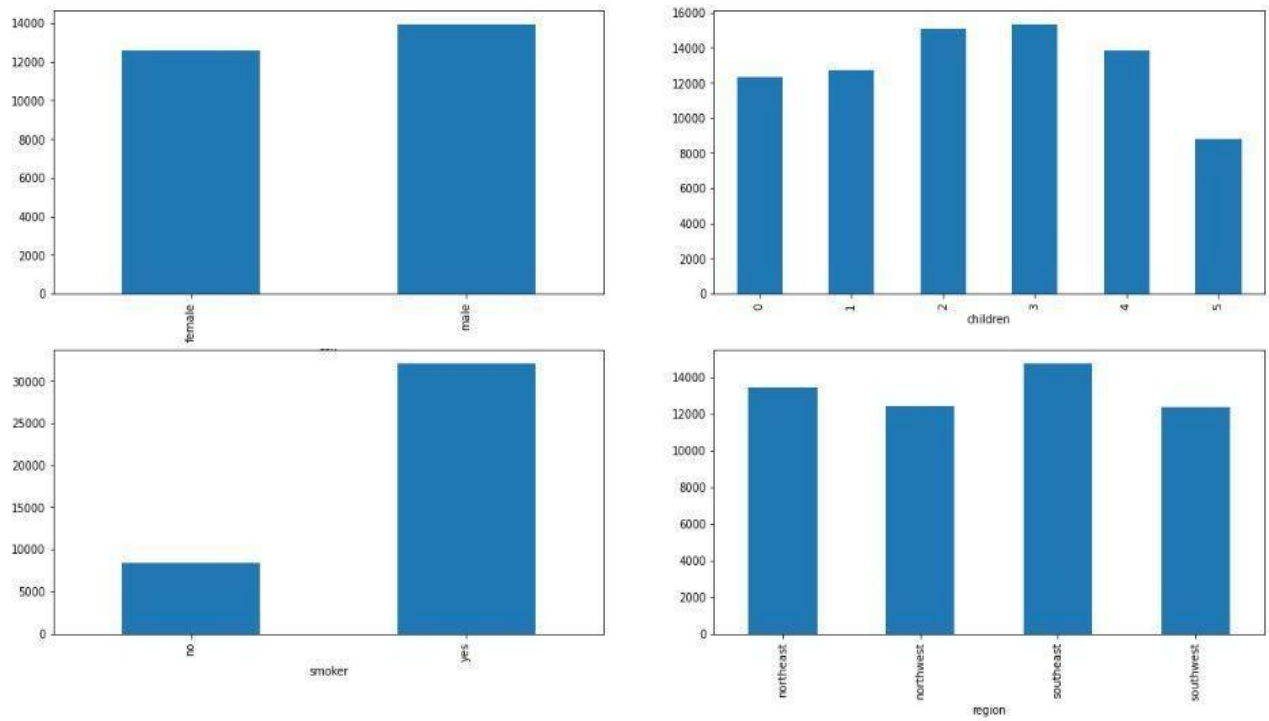

Fig 4.2 Analysis of Premium

The ROC curve is the graphical representation of the performance of the model in separating high and low premium policies.

4.3 Interpretation:

AUC: It measures the model's capacity for distinguishing between high premium policies and low premium policies.

AUC = 0.5: Model is no better than random guessing.

AUC = 1: Model is perfect at distinguishing between high premium policies and low premium policies.

AUC > 0.7: Model is good.

AUC > 0.8: Model is excellent.

ROC Curve Shape:

If the curve is near the top-left, the model is good at distinguishing between high premium policies and low premium policies.

If the curve is near the diagonal, the model is no better than random guessing.*4.4 Bar Graph Interpretation*

Our main method for analyzing the way the model is allocating costs across different demographics will be the use of a bar graph. Rather than trying to analyze numbers in a spreadsheet, this type of graph will allow us to see exactly where the model is "placing its bets."

How to Read the Data

Comparing the Costs: The height of each bar immediately provides us with the premium prediction for that group. It's extremely easy to immediately identify trends, such as if one type of policy is significantly more expensive than the others.

Category Breakdown: We have broken the data into three main groups to understand the behavior of the model:

Age Groups: For this, we have segments such as 18-25, 26-35, 36-45, etc. Most often, we see the greatest variance in this area.

Geographic Trends: Comparing urban, rural, and suburban areas helps us understand the model's consideration of environmental factors such as traffic density or crime rates

Policy Structure: Comprehensive coverage is compared to third-party options to ensure the price difference is logical.The graph is not just an image, but an actual representation of the logic learned by the machine. Most obviously, we can see the increase in premium cost as the policyholder gets older, reflecting the increased medical risks. Another interesting trend we noticed was that urban locations tended to have a higher price, possibly reflecting the increased likelihood of accidents. Perhaps the most surprising trend, however, is that the machine tends to price comprehensive coverage lower than we expected, which could reflect the idea that people who opt for better coverage are probably better drivers.

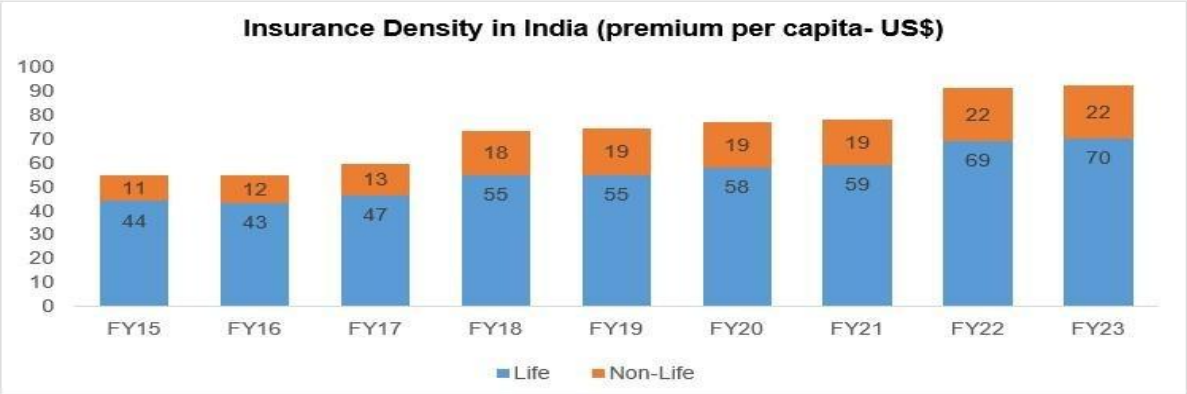

Fig 4.4 Bar Graph Interpretation

5. Conclusion and Future work

Superior Models: Gradient Boosting, specifically XGBoost, and Random Forest have been identified as the most effective models, which provide superior accuracy in the prediction of medical costs, even with smaller datasets.

Key Predictors: Age, smoking habits, and Body Mass Index (BMI) have been identified as the most critical factors that influence premium costs.

Performance Metrics: Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) have been commonly used metrics for validating the models, with the superior models achieving an error range of ±10%.

Actionable Insights: Machine learning models have helped insurers move beyond risk segments to personalized pricing. Adverse selection risks have been reduced.

Future Work:

1. Investigate other features (driver information, vehicle information, location information)

2. Test other algorithms (gradient boosting, neural networks, ensemble methods)

3. Put the model into a production setting

4. Continuously monitor and update the model

5. Create methods to interpret the model's results

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