Assessing the sustainability of General Insurance Business through Real Time Monitoring of KPIs using Recurrent Neural Network

S.R.Pranav Sai[*], **Ajay Singh Pawar, Satya Sai Mudigonda, Phani Krishna Kandala, Pallav Kumar Baruah**

Abstract: A company's sustainability is driven significantly by its operational efficiency. Operational efficiency plays a significant role in the growth and the profitability of a company. Thus, operational efficiency of a company forms the basis for the metrics known as the Key Performance Indicators(KPIs). These KPIs bridge the concept of performance an operation and a means to measure the same quantitatively. In this work, we used Recurrent Neural Network (RNN) with the Long Short Term Memory(LSTM) cells for projecting the public disclosure data of select General Insurance(GI) companies operating in India to the future. We use this data to calculate the KPIs pertaining to the operations of general insurance companies and calculate how the operations of the GI company affect its performance at various levels. Since this analysis is done for the projected data, we get a framework to assess the sustainability of the GI companies by monitoring these KPIs in real-time. The complex RNN and LSTM algorithms were implemented with the help of the Google Colaboratory platform by using the GPUs of the Google Hardware with the help of the Cloud Computing framework.

Keywords: Actuarial Analysis, General Insurance, Public Disclosure, RNN, LSTM, Google Colaboratory

I. INTRODUCTION

This A Neural Network refers to a computing system inspired by the naturally occurring network which constitutes the human brain. The system draws from the concept of experiential learning and learns how to perform tasks based on previous observations or examples. Given a dataset, the system is designed to capture and learn any underlying patterns within the data. We utilise the quarterly data disclosed by insurance companies with the intent of running it through a neural network. Upon analysis, it can identify trends within the data. Extrapolating into a future time frame, we can project the factors needed and calculate the requisite KPIs.

In meeting business objectives and optimising operational efficiency, a company needs to transcend subjective viewpoints and rely on tools with scientific backing. In this paper, we delve into the study and application of such a tool known as a Key Performance Indicator (KPI). Given a certain operation in the company, KPIs quantify the manner in which the operation is executed. With respect to line of business, topographical area and other such factors, there are various KPIs utilized to evaluate a company's functioning. In this paper, we shall consider a broad range of 18 KPIs drawn from the work of (Shiu, 2004). They can be dissected into two distinct classes in which one class indicates the performance while the other measures the performance of various underlying operations at various levels. Firming up a bond between the two methods of classification, we can now consider the impact of the firm's performance with respect to the given KPIs. Our KPIs are found through utilising a fully connected neural network and projecting the given data into the needed future time frame. Significantly, we arrive at our results by determining the sensitivities of the KPIs with respect to the company's performance.

The paper is divided into 12 sections. Section 2 captures the motivation behind this work and potential advantages. In the Section 3, we delve into the concept of Key Performance Indicators (KPIs). Section 4 Classifies the KPIs into 2 and gives the definition of each of the KPIs considered in the work. Section 5 takes a look at the data and the data sources and also give a comprehensive framework for assessing the sustainability of the general insurance company using the KPIs. In section 6, gives the detailed explanations for the RNN and the LSTM framework. In Section 7, we discuss the steps involved in implementing the RNN and LSTM framework on our dataset. In Section 8, we tabulate and draw inferences from the results that we obtain. Section 9 discusses the challenges faced and the limitations of this model. Section 10 lists down the next steps which are going to be taken up post this work. Section 11 acknowledges the help offered by several people and our institution. Section 12 gives the list of references.

S.R.Pranav Sai*, Doctorial Research Scholar, Department of Mathematics and Computer Science, Sri Sathya Sai Institute of Higher Learning, Puttaparthi,, India Email: srpranavsai@sssihl.edu.in

Ajay Singh Pawar, Master's Student, Department of Mathematics and Computer science, Sri Sathya Sai Institute of Higher Learning, Puttaparthi India Email: ajay257223@gmail.com

Satya Sai Mudigonda, Senior Tech Actuarial Consultant, Hon. Professor in Department of Mathematics and Computer Science, Sri Sathya Sai Institute of Higher Learning Puttaparthi, India Email: satyasaibabamudigonda@sssihl.edu.in

Phani Krishna Kandala, Visiting faculty, Sri Sathya Sai Institute of Higher Learning, Puttaparthi, India
Email: kandala.phanikrishna@gmail.com

Dr. Pallav Kumar Baruah, Associate Professor, Department of Mathematics and Computer Science, Sri Sathya Sai Institute of Higher Learning, Puttaparthi, India Email: pkbaruah@sssihl.edu.in

II. MOTIVATION

Capturing unseen patterns from the underlying data, Neural Networks are efficient systems and represent a fast and efficient method of analysing certain features from our data. Upon analysis, we expand our data set by projecting into the future. Specifically, we shall delineate its importance in projecting KPIs for an insurance company. Padding up the risk of the entire economy, the insurance industry is pivotal and must be governed effectively in a streamlined manner. For developed countries, the insurance industry has approximately an 8% GDP penetration which can be seen from the reports of (Gonzalez,2018). In particular, the Indian Insurance Industry represents 59 companies subdivided into 24 life insurance firms and 36 non-life firms. Incorporating both private and open division companies, India represents a growing economy with premiums sizing up 3.69% of the country's GDP. From a GDP penetration of 2.71% in the year 2001 up to 3.69% in 2017, India has witnessed a steady, enduring growth in its Insurance Market. India is slated to achieve a market size of 25 lakh crores in INR by the close of 2020. Our interest lies in exploring and achieving a highly efficient and productive method of working in furthering and achieving the targets set out for the Indian Insurance Industry.

III. Steps to derive the KPIs KEY PERFORMANCE INDICATORS (KPIS)

Key Performance Indicators quantify and evaluate the performance of a company in an objective manner. Representing a vital cog in the decision-making process, they help anticipate trends in requisite factors and draw inferences which helps company make informed decisions. KPIs can take on discrete, continuous forms dependent on the factor being evaluated. Measuring the performance of a company on various fronts, KPIs highlight the regions in which a rise in productivity is required with the intent of optimizing the operational efficiency.

A. The Steps to derive the KPIs

The following steps must be performed in order to get the KPIs for a company.

Figure 1 – The steps to derive the KPIs

- List the various operations of the company at all levels.
- For each of the operations, get to know all the steps and processes involved.
  - It is ideal to deal with downside risks since we are talking about performance improvements.
- List various risks under each of the operations.

- Formulate the various parameters that measure each of the underlying risks.
- Only the quantifiable risks can be analysed by the models.
  - It is important to find out how to derive these parameters from the available data factors.
- Once the parameters are in place, they are grouped to form the Key Performance Indicators for that process.

IV. KEY PERFORMANCEINDICATORS (KPIs)

A. Independent Variables

As discussed above, KPIs refer to informative variables which quantify and measure an organization's performance. Here, we define and describe various KPIs while exploring the relationship between each KPI and the company's performance.

1) Unexpected Inflation (UI)

Unexpected Inflation highlights the inflation which is experienced above or below the rate which is anticipated for a given time period. Be it inaccuracy in the model's assumptions or unforeseen circumstances such as a natural calamity, unexpected inflation is always present to varying degrees when applied in the real world. The given KPI detects and arrives at the exact figure so as to aid decision-makers in estimating the real value of the profits earned accounting for unexpected inflation. By doing so, the company gains a rounded perspective with regard to the actual accounting figures. Specifically, the underwriting department assumes a certain inflation figure in the calculation of premiums and other primary operations. The variable carries a heightened level of importance due to its ability to have a significant negative impact on a company's financial state.

2) Interest rate change (IRC)

This indicator aims to quantify the shift or change in the rate of interest. It can potentially lead to a significant change in the value of the insurer's assets and liabilities which consequently has an impact on the firm's profit margins. Be it fixed level investments or debentures, the investment portfolio maintained by a company is vulnerable to small changes in the interest rate. Generally, market trends have suggested that most insurers in the Indian insurance industry suffer underwriting losses which is compensated by a healthy flow of investment income. Actuaries utilise the immunization conditions given by Redington in order to effectively predict the potential effect of an interest rate change. Hence, the ability of a change in the interest rates to affect the firm's core profit-making areas renders it an important variable to considered in decision-making.

3) Interest rate level (IRL)

By definition, the rate of interest is considered the cost of repaying a loan as a predetermined proportion of the principal amount received from the lender. Determined through

the monetary policy outlined by the RBI, it carries important implications and repercussions for firms and decision-makers alike. The level at which the interest rate is set provides a financial foundation with which a company can make business decisions and plan for a future time frame. Naturally, a lower interest rate would be preferred as it signals an ease and affordability in investments and growth opportunities for any company. Similarly, a high interest rate provides a negative business outlook as it renders taking a loan expensive and makes investments and expansions plan a risky endeavour.

4) Equity Returns (ER)

Stocks or equities are investments made in listed companies for an ownership stake in the company proportional to the capital invested. A return in the investments made in such stocks is referred to as equity returns. Due to the volatile nature of the stock market, investments made are vulnerable to abrupt slides in market value and depreciation. For the above reason, companies generally protect their investment portfolio by maintaining only a small fraction of the investments in the form of stocks. This ensures that the company maintains a fair balance of earning incredible equity returns while protecting the solvency margin of a company in the case of massive losses. The potential of high returns turns this metric into an important once which can heavily influence the level of investment income that an insurer earns from its portfolio.

5) Company size (LOGTA)

In various scenarios, assessing the performance of a firm requires a keen understanding of the size of a firm and its growth potential. By convention, this metric calculates firm size by solving for the natural logarithm of the insurer's total assets. A "big" firm with relatively valuable assets can take advantage of economies of scale and achieve optimized efficiency by cutting costs due to specialisation and comparatively heightened capability. By quantifying the total assets of a company, one can analyse the resources available and the firm's ability to bail itself out in times of financial emergency.

6) Reinsurance dependence (RCTA)

Insurance theory suggests the need for a level of reinsurance for insurers to achieve security from scenarios in which high claims pay-outs threaten the company's ability to fulful its obligations. Reinsurance entails passing on a proportion of the risk for a given insurance policy. In reducing the risk born by a firm, it frees up additional reserves to be utilized as investments. Yet, the potential reduction in the scale of losses carries the negative implication that a share of the profits is also given to the reinsurer. Clearly, it is imperative that a minimal level of reinsurance is essential and yet that a high degree of dependence on reinsurance blocks the potential to earn high profits and grow as a firm. Thus, this metric is one of fundamental importance as it defines the company's financial vision and risk-taking ability.

7) Leverage (TNTPSF)

For each insurance policy, the insurer is required to maintain a fraction of the premium amounts in the form of reserves to ensure that any claims pay-outs can be handled with the necessary financial settlement. The level or proportion of premium income that is held as reserves is referred to as the leveraging position of a firm. In the eyes of the accountant, the reserves are classified as either unearned premium figures or outstanding claims amounts. The latter refers to a long-term facility to provide financial security to the insurer whereas the former is a reserve maintained for the policy time period after which it is accounted as earned premium. This KPI is reflective of how the company balances the profit-making operations with the ability to settle claims in an efficient, hassle-free manner.

8) Investments (TAISF)

This metric refers to the performance of the investment portfolio maintained by a firm. As delineated in prior sections, this source of income is essential to turn a loss-making underwriting segment into an overall profit. Through long-term investment, stocks, bonds and public sector securities, a company's investment portfolio is a diversified range of investments made in various financial instruments. This variable denotes the efficiency and performance of the investment portfolio maintained by a company and is positively related to the profitability of an insurer.

9) Solvency margin (NANPW)

Reflective of an insurer's ability to settle and pay its financial commitments in the long run, this variable evaluates the long-term financial strength of an insurer. The implications of disregarding this factor are significant as an insolvent company is considered bankrupt. With the objective of protecting stakeholders and customers of an insurance company, the Insurance Regulatory Development Authority of India(IRDAI) legally requires additional capital to be maintained in the form of a solvency margin at 150%. This mandate acts as an efficient regulatory measure to protect against the inherently unpredictable nature of the insurance industry. Large-Scale pay-outs may be necessary and to ensure safety for the customers, the IRDAI legally encourages companies to maintain favorable solvency margins.

10) Stability of underwriting operation (ACGPW)

Underwriting represents the fundamental operation for an insurance company. It functions as an end-end process covering the life cycle of a insurance product by calculating premium amounts and structuring the payments to reflect the risk born by the insurer and provide a fair platform for the purchase and sale of insurance products. The chief aim of the underwriting process is to eliminate excess and inadvisable risk from being given coverage in an insurance policy. The efficiency and performance of this key process is captured by this indicator which evaluates the core strength for an insurer.

11) Liquidity (TLLA)

Liquidity represents the short-term variable parallel to that of the solvency margin. It is defined as the capability of an insurer to fulfil its obligations in the near future. Essentially, this translates into the ability of a company to convert assets readily into cash to meet its short-term liabilities. The variable quantifies the difference between the assets and the short-term liabilities and evaluates the financial strength in the short run. A company with a favorable liquidity position is primed to achieve operational efficiency and earn profits.

12) Stability of asset structure (CAM)

The asset structure of a company refers to the division and segregation of a company's assets. By definition, an asset is an instrument of value for a company. The assets must be utilized in the optimal manner to earn a profitable stream of income for the company. Key to achieving the above mentioned high returns are effectively classifying the assets into various categories such as the property sector, government securities and stocks to optimize earnings from the asset base. The structure of division of assets is an indicator of a company's business approach and evokes confidence from its stakeholders. Typically, it is considered prudent to not make major changes in the assets structure so as to convey stability and strength. Otherwise, it leads to unfavorable market speculation which can impact the company negatively. Thus, this metric represents a marker of the solidity and stability of an insurer.

13) Underwriting profits (UP)

As outlined above, the core underwriting operation for an insurer generally represents a loss-making endeavour which is typically compensated for by investment income and turn in an overall profit. Delving into the specifics, underwriting loss entails higher claims amounts being handed out than premium income being earned. In the modern Indian insurance industry, Bajaj Allianz stands out as the chief exception to this oddity as the company has consistently functioned with a profitable underwriting process. Key to their success has been a focus on digital excellence coupled with a heightened operational efficiency. Underwriting profitability is possible for Indian insurers with a paradigm shift from traditional methods to modern, scientific modes of functioning. This metric carries a direct link to the profitability and success of an insurer as it evaluates the capacity to earn profits from the fundamental underwriting operation.

14) Insurer type (IT)

The given KPI is qualitative as it provides a context to the objectives and potential of an insurer in the non-life industry. The classification is dependent on which insurance sector the company operates in while analysing the various lines of business that it caters to. Chiefly, it classifies the company as either a life insurer or as a non-life insurer while further classifying which subcategory it belongs to. Given the type of insurance product, one can have expert general insurers, composite insurers, multi-line insurers as well as reinsurers such as GIC India. The indicator is useful in decision-making due to the perspective it provides in understanding the areas that a company operates in. Further, it helps one delineate the typical risks faced and opportunities available for growth.

A. Dependent Variables

1) Percentage Change in Shareholder Funds (PCSF)

This KPI is indicative of the company's overall performance and its financial standing. An increase or decrease in the shareholder funds is reflective of a positive or negative performance respectively in a given financial year.
It is formulated as:-

$$PCSF = 100\ (SF_t - SF_{t-1})/SF_{t-1}, \tag{1}$$

where: -

- SF_t is defined as the value of the Shareholders' fund estimated at time t.

2) Investment Yield (IY)

This dependant variable evaluates the performance of the investment portfolio that the company maintains. Inclusive of returns earned on various investments in different categories over a fixed period of time, the investment yield is positively correlated with the profitability of the company.

$$IY = 100* NII / (0.5 * (TA_t + TA_{t-1})) \tag{2}$$

where:-
- NII refers to the Net Investment Income
- TA_t is defined as the Total assets at a given time t

3) Return on Shareholder Funds(RSF)

This metric determines the amount of funds given back to the shareholders or the capital invested back into the company. This metric provides an understanding of whether the company has generated enough profit to make these payments to its shareholders.

$$RSF = 100* PBTD / (0.5 * (SF_t + SF_{t-1})), \tag{3}$$

where: -
- PBTDs stands for profits before tax and dividends

V. THE DATA AND FRAMEWORK

In our study, we work with 4 different general insurance companies operational in India. The data we have for our study is obtained from the public disclosures of these insurance companies from the Insurance Regulatory and Development Authority of India (IRDAI). In this study, we consider 27 different factors from the public disclosures for our analysis.

We then analyse this data and project them using Neural Networks and calculate the Key Performance Indicators for our analysis. Thus after defining each of the Key Performance Indicators(KPIs) in the company, we put forth the framework for enhancing the operational efficiency of a general insurance company.
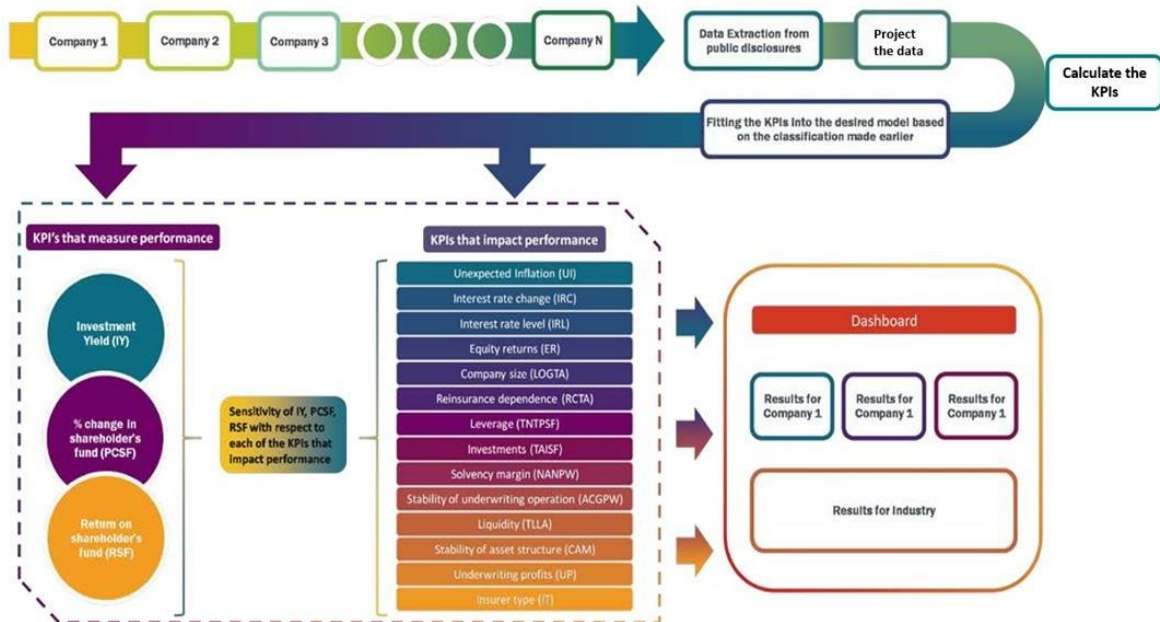

Figure 2 – The overall framework

The 27 factors used

1 Investment Income
2 Profit before taxation
3 Funds of shareholders
4 Total assets
5 Total Reinsurance
6 Total Reserves
7 Total Investments (Affiliated)
8 Net assets
9 Total Net Premium written
10 Total Gross Premium
11 Liability total
12 Total Liquid Assets
13 Total Cash
14 Total Bonds
15 Total Equity
16 Total Investments
17 Total Debt
18 Other assets
19 Total Prepayments
20 Total Reserves - Reinsurer's share
21 Total Premiums earned
22 Total Claims incurred
23 Operating expenses total
24 Discount adjustments
25 Changes in reserves
26 Provision for unexpired risks
27 Other technical income

VI. RECURRENT NEURAL NETWORKS AND LSTMS

A. An Introduction to Neural Networks

A Neural Network refers to a series of programming algorithms that endeavours to capture underlying relationships in a given dataset. The process through which it happens attempts to mimic the system of neurons operating within the human brain. In a sense, neural networks can receive sensory data and provide an interpretation from the machine perspective. They are capable of spotting numerical patterns enclosed within vectors and translating them into tangible, everyday data – be it pictures, audio or video.

An artificial neural network refers to a connectionist system comprised of a large number of parallel processing units called neurons which work in tandem to present a solution to the given problem. Similar to human optic nerves, the first tier of processors is responsible for processing the raw input and sending a refined version onto the next tier. Iteratively, each succeeding tier is responsible for refining the output received and sending it onto the next tier. The output produced by the final tier is known as the system output.

B. Recurrent Neural Networks (RNN)

A Recurrent Neural Network represents a Neural Network in which output received from the preceding step is fed in as input for the present step. In a sense, it can be considered a generalized version of a feedforward neural network coupled with the additional benefit of retaining memory of previous steps internally. A common occurrence in nature, a recurrent

neural network performs an identical function for each input it receives with each step depending on the output of the previous step. Upon producing an output, the data is copied into its internal memory before being sent back in as input into the network as input for the next step.

Figure 3 – An unrolled RNN

With the added advantage of maintaining an internal memory, RNNs are capable of processing sequences of varied inputs. This provides for a plethora of applications into the fields of speech recognition and handwriting recognition. Within a RNN, all the inputs are dependent upon each other whereas inputs are independent of each other in any other standard neural network. The above diagram illustrates the manner in which a RNN process data from the first state until the last state. In the 1st step, the network receives X(0) as the first input and produces an output of h(0). h(0) and X(1) act together as the combined input for the next step. This produces an output of h(1) which acts as the input for the next step along with X(2). Iteratively, the process continues similarly till the last step in which the output represents the system output.

For any given state, we can represent the output as below:

$$h_t = f(h_{t-1}, x_t)$$

(4)

Next, we apply the activation function as shown below:

$$h_t = \tanh (W_{hh}h_{t-1} + W_{xh}x_t)$$

(5)

$$y_t = W_{hy}h_t$$

(6)

In the above equation, W stands for the weight, h represents the single concealed vector, W_{hh} is the previous weight, W_{hx} denotes the current input weight whereas tanh represents the activation function. The activation function is responsible for the implementation of a non-linearity which contract all the activation to the range [-1,1].

The output of a given state can be characterized as below:
In the above formula, Y_t denotes the output state and Why represents the output weight.

C. Benefits and Drawbacks of using Recurrent Neural Networks

In this section, we set out to delineate both the advantages and disadvantages of using recurrent neural networks. The first benefit that RNN provides is its ability to model a given sequence of data in which each element is related to the previous element. After all, the above benefit characterises the essence of a RNN. An additional benefit of using RNNs is that they can be used along with convolutional layers which provides for an extended
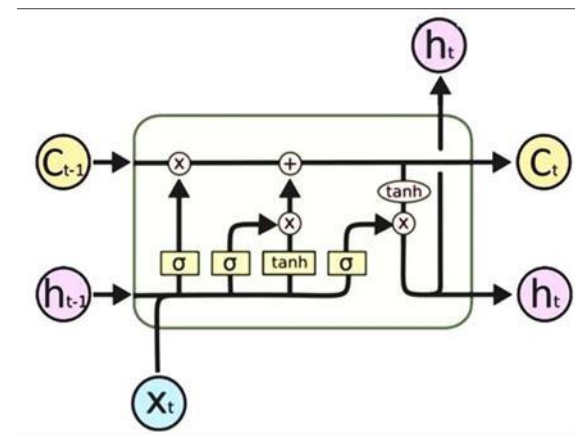
effective pixel neighbourhood. Conversely, there are drawbacks of using RNNs which must be kept in mind. Firstly, RNNs must be trained in an effective manner which can be difficult to do. Also, the user may experience gradient vanishing along with exploding problems. The final drawback would be that it is limited to moderately sized sequences of data due to the presence of tanh or relu as the activation function.

D. Long Short-Term Memory

An altered version of RNNs, Long Short-Term Memory Networks represent a more efficient way to commit previous data into the internal memory. Also, it removes the vanishing gradient problem which was one of the major drawbacks of RNNs. Long Short-Term Memory Networks are designed to efficiently categorize, process and forecast time series along with time lags of undetermined durations. well-suited to classify, process and predict time series given time lags of unknown duration. The model is trained by utilizing a method called back-propagation.

Figure 4 – The LSTM Architecture

E. The Crux of LSTMs

The crux to understanding the concept of LSTMs is the cell state which can be seen in the below diagram. The cell state can be seen to be the distinct horizontal line which is boldly ascribed. It functions in a manner similar to that of a conveyor belt. Apart from a few linear interactions, information flows down the entire chain unchanged.
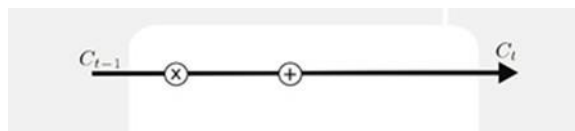

Figure 5 – The baseline carryinng the information between 2 LSTM units

It is to be noted that the network retains the authority to either add or delete information to the cell state while kept in check by regulatory structures known as gates. Through a gate, it is optional to let information through. Comprising of a sigmoid net layer along with a pointwise multiplication operation, the structure of a gate can be seen as illustrated below.
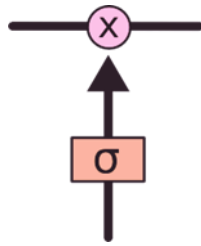
Figure 6 – The sigmoid layer

From the sigmoid layer, we receive outputs ranging from zero to one which describes the extent to which a given component must be let though. Here, zero represents the null value blocking any passage of information with 1 at the other end of the spectrum allowing full passage of information. An LSTM consists of 3 gates which safeguard and control the cell state.

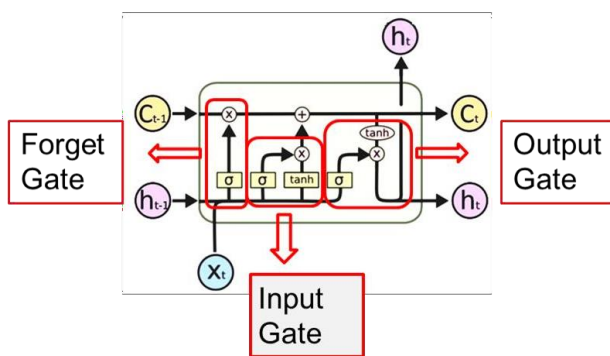#### F. Deriving the formulae for LSTM Gates

Figure 7 – LSTM gates

- **Input gate** – In this gate, the primary operation is that of finding out which value from the input is to be taken and is to be utilized in altering the internal memory. The sigmoid function provides the output value ranging from 0 to 1 which decides how much information is to flow through. Also, the tanh function provides a weightage to each of the values passing through while quantifying a degree of important between -1 and 1.

$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \; + \; b_i\right)$$
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \; + \; b_C)$$

$$(7)$$

- **Forget gate** – In this gate, the task at hand is that of deciding which data is to be removed from the block. The sigmoid function views the preceding state (ht-1) along with considering the given input (Xt). It then provides an output which ranges from 0(to be omitted) to 1(to be kept) for every number in C_{t-1}.

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \; + \; b_f\right)$$

$$(8)$$

Output gate – In this gate, both the given input and the block memory are used in determining the output. In this case, the sigmoid function uses the same method of producing an output between 0 and 1 to decide how much information is to be let through which tanh is used as weight function ascribing a value between -1 to 1. This is further multiplied with the output produced by the sigmoid function to ascertain the degree of importance.

$$o_t = \sigma\left(W_o \; [h_{t-1}, x_t] \; + \; b_o\right)$$
$$h_t = o_t * \tanh\left(C_t\right)$$

$$(9)$$

VII. METHODOLOGY

In this section we give a step-by-step explanation on how the above RNN and LSTM networks were implemented to project our given data set. As mentioned above, our data set consists of the public disclosures of 4 General Insurance companies operating in India. These 4 companies in our study are named as Insurer A, Insurer B, Insurer C and Insurer D. There are 27 factors that we have considered from the given data set for each of the companies. The data was feature scaled using the minmax scalar. The scaled data was then fed into an RNN framework with 100 LSTM cells followed by a fully connected layer with 28 neurons (dimension of the data + the factor of time). The activation function used was ReLU activation function, the optimizer used was the Adam optimizer and loss function used was mean squared error. We used 120 continuous samples to predict the next sample in our data set. We arrived at 120 continuous samples as a benchmark following the advice of the industry experts. The batch size considered was 32 and the algorithm was trained for 150 epochs, with the learning rate of 1%.

The entire framework was coded on the Google Colaboratory platform. Colab notebooks execute the algorithms on the Google cloud servers. This means that we can leverage on the power of Google hardware including GPU's and PPU's regardless of the in-house facility we would have.

VIII. RESULTS

The data was projected for 4 different General Insurance companies in India. About 27 different factors were considered in the data for projecting to the future. Out of these 27, we consider two factors namely, Total assets and shareholders' funds. The following 4 graphs show the trends of these 2 factors with respect to time. These 2 factors are measured in the units of INR. The dotted line in each of the graphs divides the graph into the past data's trend and the projected data's trend for these 2 factors with respect to time.
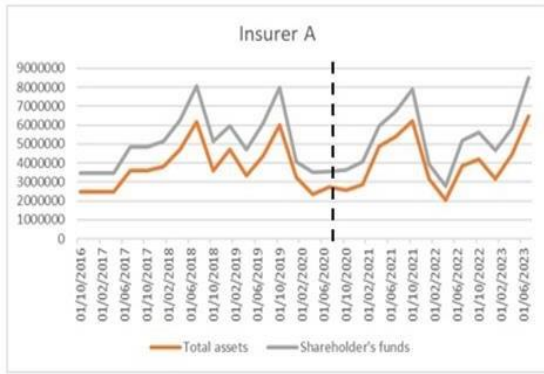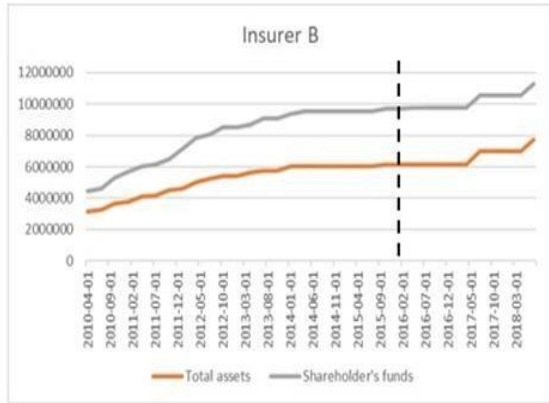
Figure 8 – Insurer A
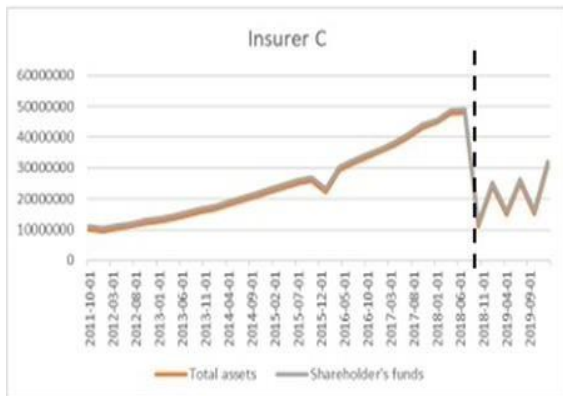

Figure 9 – Insurer B
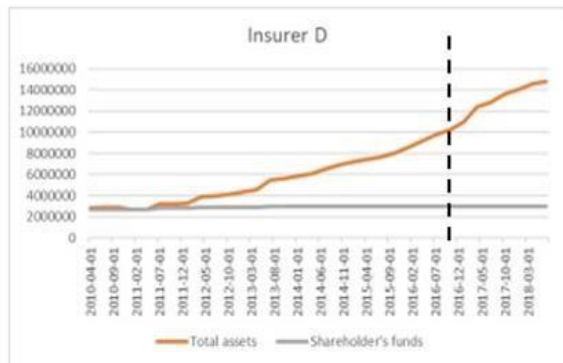

Figure 10 – Insurer C

Figure 11 – Insurer D

The following 4 tables are correlation matrices. These matrices show how each of the dependent KPIs (which are the means of indicating the performance of the company), sensitive to each of the independent KPIs (which directly affect the performance of the company) for all the 4 companies considered individually.

Table- II: KPIs – Insurer A

Insurer A	IY	PCSF	RSF
logta	-0.97411	0.948702	-0.77936
RCTA	-0.81372	0.277384	-0.16626
TNTPCF	0.524647	-0.76938	0.982228
TAISF	-0.52996	0.641654	-0.9699
NANPW	-0.41292	0.60531	-0.95188
TLLA	-0.10032	0.32923	-0.17499
UP	0.817484	-0.98821	0.807226
ACGPW	0.411967	-0.61625	0.946185
CAM	-0.94528	0.907102	-0.82044
IY	1	-0.75601	0.636208
PCSF	-0.75601	1	-0.8019
RSF	0.636208	-0.8019	1
IRL	4.82E-17	-1.08E-16	-1.24E-16
ER	0	-4.06E-17	-1.24E-16

Table- III: KPIs – Insurer B

Insurer B	IY	PCSF	RSF
logta	-0.98623	0.98612	0.926417
RCTA	-0.63988	0.697504	0.743695
TNTPCF	-0.99233	0.990363	0.915402
TAISF	-0.97595	0.984842	0.953643
NANPW	0.988496	-0.99533	-0.9399
TLLA	-0.98282	0.990467	0.892013
UP	0.789462	-0.83783	-0.87951
ACGPW	-0.97312	0.972502	0.923515
CAM	-0.95454	0.969738	0.890812
IY	1	-0.99447	-0.87863
PCSF	-0.99447	1	0.909654
RSF	-0.87863	0.909654	1
IRL	1.02E-16	1.50E-16	3.65E-15
ER	1.15E-16	1.28E-16	3.65E-15

Table- IV: KPIs – Insurer C

Insurer C	IY	PCSF	RSF
logta	0.024313	0.064707	-0.14049
RCTA	0.995086	0.877942	0.992182
TNTPCF	-0.93448	-0.82439	-0.98147
TAISF	-0.97544	-0.85855	-0.99802
NANPW	0.965775	0.816257	0.985966
TLLA	0.488416	0.485418	0.368222
UP	0.989297	0.882093	0.998688
ACGPW	0.983916	0.925235	0.961373
CAM	0.89245	0.601127	0.815313
IY	1	0.866426	0.982342
PCSF	0.866426	1	0.870425
RSF	0.982342	0.870425	1
IRL	2.46E-16	-8.78E-17	4.27E-17
ER	2.68E-16	-6.59E-17	-1.76E-16

Table- V: KPIs – Insurer D

Insurer D	IY	PCSF	RSF
logta	-0.44279	0.99088	0.953586
RCTA	-0.55658	0.956069	0.99686
TNTPCF	-0.42408	0.990902	0.96857
TAISF	-0.80718	0.803701	0.960394
NANPW	0.641752	-0.09113	-0.40248
TLLA	0.291268	-0.98422	-0.88461
UP	0.372856	-0.99848	-0.948
ACGPW	0.411662	0.198139	-0.10381
CAM	-0.61724	0.919756	0.995367
IY	1	-0.34153	-0.62001
PCSF	-0.34153	1	0.935118
RSF	-0.62001	0.935118	1
IRL	-2.42E-16	-6.33E-17	-8.11E-17
ER	-1.45E-16	0	3.04E-17

We have thus tabulated the results of the 4 insurance companies with regard to the correlations between the dependent and the independent KPIs from the data. This will enable us to make inferences on how each of the underlying operations impact the performance of the company. This is done by giving weights to the correlations based on the importance given owing to the company's business structure of the company along with its size, risk appetite and the external environment. The table below gives a better explanation of how each of the independent KPIs affect various operations and the overall performance of the company.

Table- VI: The determinants of performance

No.	Determinants of performance	What stand affected	Relation with performance
1	Unexpected Inflation	Claims, Expenses, Provisions	Negative
2	Interest Rate Change	Assets, Liabilities, Claim Costs	Depends on the duration of the assets and the Liabilities
3	Interest rate level	Investment Earnings	Positive
4	Equity Returns	Investment Earnings	Positive
5	Underwriting Cycle	Underwriting Profits	Intermediate
6	Company Size	Costs due to economies of scale	Positive
7	Reinsurance Dependence	Profits	Negative
8	Leverage	Equity	Positive till the optimum capital structure and negative thereafter
9	Affiliated investments	Insolvency risk increases	Negative
10	Solvency Margin	Reserves	Positive
11	Stability of underwriting operations	Premium rates	No prior expectations
12	Liquidity	Investments	Positive
13	Stability of asset structure	Assets	Positive
14	Underwriting Profits	Profits	Positive
15	Insurer Type	Business Mix	Indeterminate

IX. CHALLENGES AND LIMITATIONS

We are working with the public disclosures of a General Insurance company which is available with the Insurance Regulatory Development Authority of India (IRDAI). Though the data is publicly available it is not readily usable for any sort of analysis. We must go through thousands over the years to extract the data points which we require. These data points should further be put into a suitable template to make them ready for the analysis. Thus, to do an analysis for all the general Insurance companies in India the data pre-processing would involve a lot pf time and expertise. of company records to get the data required and put them in a structured format. The model projected the company specific factors, but the model to work efficiently even the economic factors considered should be projected with the same accuracy. The economic factors are dependent on several direct and indirect factors across the globe. Thus, these can't be projected with the same degree of accuracy. In our model we consider the economic factors to be constant for the time period of projection. In this model we build the framework using 17 different

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736

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Key Performance Indicators(KPI's). These KPI's are obtained from a pre-existing literature (SHIU, 2004) which was based on the study of the General Insurance companies in United Kingdom(UK). Thus, these KPI's may not readily reflect the performance of a GI company in an Indian context. Also, the factors affecting the performance of the company would vary for different companies. So, we cannot use a "one-size-fits-all" approach for building the same. Therefore, these factors should be tailor-made to the company's size, line of business, risk appetite and other important parameters.

X. NEXT STEPS

The following are the next steps which we have planned as a part of our research problem. We plan to:

- Acquire the data of all the General Insurance companies and derive and calculate a comprehensive set of KPI's pertaining to the Indian framework.
- Expand the above model to the data for all these general insurance companies.
- To extend the work to other lines of business such as health and life.
- To build a comprehensive dashboard framework to analyze and visualize the data to aid in decision making.

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AUTHORS PROFILE

S.R.Pranav Sai – He is a doctoral research scholar in Sri Sathya Sai Institute of Higher Learning in the field of Actuarial sciences. His area of research includes Enterprise Risk Management, Operational Efficiency of insurance companies and IFRS 17. He is an Actuarial data science expert and has published research papers in international journals.

Ajay Singh Pawar – He is currently involved in research projects as part of the Master of technology in computer science in Sri Sathya Sai Institute of Higher Learning. He has a master's in science in Mathematics to his credit. His areas of research are deep learning and computer vision applied to sports and financial services

Phani Krishna Kandala – He is Assistant Vice-President in a leading Re-Insurance company. He is an active researcher in the field of actuarial data science. He has completed his Masters degree in mathematics and has done his M.Tech. in computer science. He has published several research papers and has presented in various national and international conferences

Satya Sai Mudigonda - A Senior Tech Actuarial Consultant providing services in USA and India. With a wide skill set, he managed numerous multi-million-dollar international assignments for major insurance companies across the globe. He is an honorary professor in Sri Sathya Sai Institute of Higher Learning. He has published about fifteen papers in the field of Actuarial data science and has presented in several international conferences.

Dr. Pallav Kumar Baruah – He is an Associate Professor and the former HOD of the Department of Mathematics and Computer Science of Sri Sathya Sai Institute of Higher Learning. He has guided several research scholars in mathematics and computer science. He has numerous research publications to his credit and has presented in several national and international conferences.