DISK FAILURE PREDICTION USING BI-DIRECTIONAL LSTM IN HETEROGENEOUS ENVIRONMENTS

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ABSTRACT

Technological advancements have improved reliability and storage capacity for hard disk drives in the recent past. In the industry, many critical applications are hosted onto datacenter severs specifically for reliability and the fault tolerance they provide to these applications. Even with recent advancements in designing and manufacturing reliable hard disks, disk failures are inevitable. Statistics show hard disk failures account for approximately 82% of hardware failures in datacenters. Disks fail due to wear and tear from handling large amounts of data over a period of time. Disk failures may cause degraded performance (due to worsening I/O operations) or complete loss of data. Both performance degradation and loss of data are highly undesirable in deployment environments. Disk failures can be classified as either predictable disk failures or unpredictable disk failures such as due accidents/natural calamity. For the purpose of this research, we will focus on predictable disk failures. It is important to pre-emptively detect these predictable disk failures and provide warnings to replace degraded disks to avoid longer I/O or data corruption. This helps in optimizing datacenter operations cost while maintaining reliability. Recent studies done in this field are focused on homogeneous set of disk models citing lack of standardization in SMART (Self-Monitoring, Analysis and Reporting Technology) data between hard disk manufacturers. In reality, a datacenter will most certainly have diversified set of disks with variety of make and model. Through this research, we will study generic predictors in SMART data among heterogeneous population of disks and then propose a model for predicting disk failures using bi-directional LSTM in such heterogenous environments.

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LIST OF ABBREVIATIONS

1	ADASYN	Adaptive Synthetic
2	ANN	Artificial Neural Network
3	Bi-LSTM	Bi-directional Long Short-Term Memory
4	CPU	Central Processing Unit
5	ENN	Edited Nearest Neighbour
6	FAR	False Alarm Rate
7	FDR	Failure Detection Rate
8	GPU	Graphical Processing Unit
9	GRU	Gated Recurrent Unit
10	HDD	Hard Disk Drive
11	LSTM	Long Short-Term Memory
12	RAID	Redundant Array of Independent Disks
13	RFE	Recursive Feature Elimination
14	RNN	Recurrent Neural Network
15	RUL	Remaining Useful Life
16	SMART	Self-Monitoring, Analysis and Reporting Technology
17	SMOTE	Synthetic Minority Oversampling Technique
18	SSD	Solid State Drive

CHAPTER 1: INTRODUCTION

1.1. Background

Across the industries & governments, digitization has become a major goal. Global internet traffic has surpassed the threshold of 2 zettabytes per year. The data storage market is expected to grow exponentially due to high adoption of cloud storage technology. Social media, OTT streaming services, big-data analytics and backups are driving the high demand for quality data storage services. In such day and age, datacenters are considered as the backbone of modern technology. Indisputably, hard disk drives are the most important component in these datacenters dealing with humongous volume of data on daily basis. On an average, hard disk lasts for 3-4 years before needing replacement.

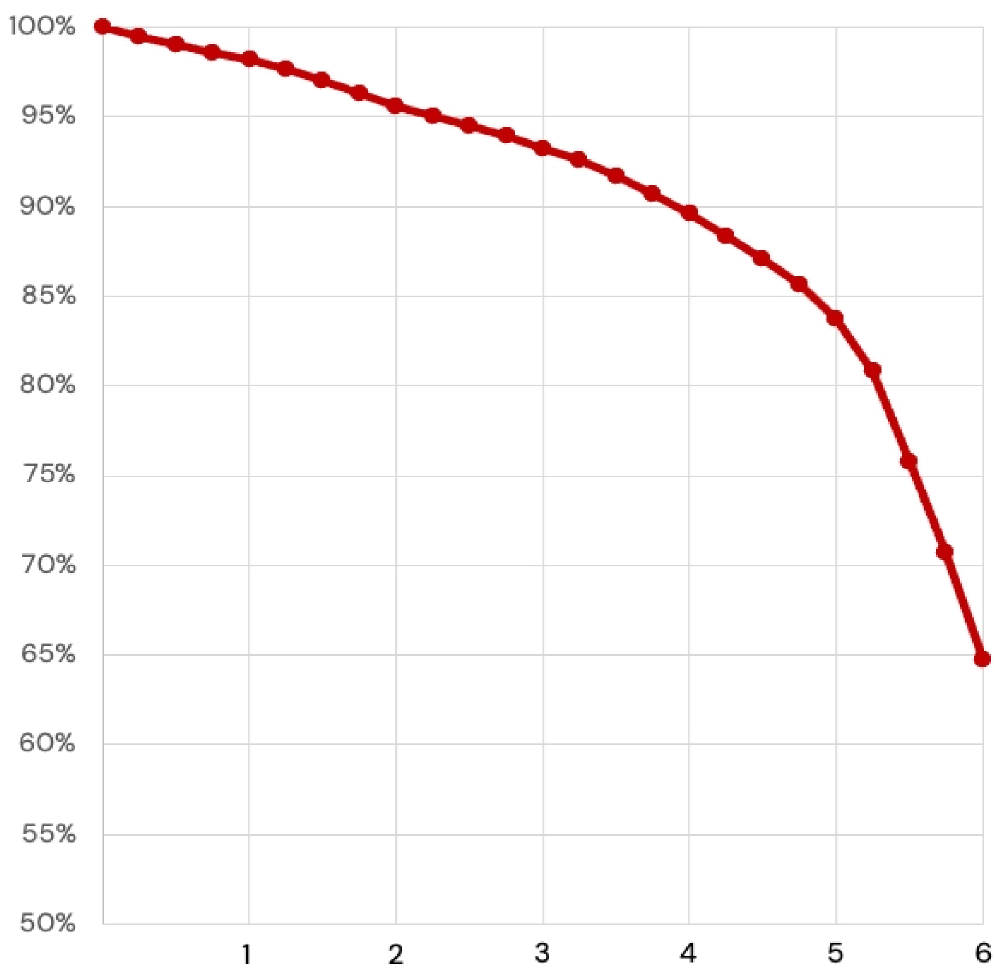

Figure 1. Hard Drive Survival Rates over years

In datacenters, disk failures are a common occurrence. Statistics show hard disk failures account for approximately 81.84% (Zhang, 2019) of hardware failures in datacenters. A hard disk failure occurs when stored data cannot be accessed due to malfunction. Disk failures may occur during normal course of operations in a datacenter or due to external factors. Disks can fail due to malware disruption or due to data corruption. Head crashes are a common cause for disk failure wherein the head of the disk that usually hovers just over the surface of the disk touch the platters or damages the disk. A head crash can cause severe damage to the disk and is a well-known risk factor. Read-write errors that are recoverable occurring frequently are early signs of wear and tear on the disk.

Disk failures can be classified into predictable and non-predictable failures. Predictable disk failure usually occurs due to regular wear and tear over time or frequent erasing attempts. Non-predictable disk failures occur due sudden power surge/Natural Calamities etc. When values reported by SMART [28] exceeds certain threshold, it can be a sign of impending disk failure. Based on these warnings, backup and replacement of bad disks can be planned. While early replacement of disks can cause waste of disk life cycle, replacing it too late may lead to loss of data.

Although, RAID implementations can help in planning and mitigating risk of data loss, it comes at the cost of additional resources. To optimize datacenter operational costs, predicting potential disk failures within a reasonable window with high FDR (failure detection rate) and lower FAR (false alarm rate) has become immensely important. Multiple research studies have been conducted to predict the disk failure using SMART attributes of each disk.

Self-Monitoring, Analysis and Reporting tool (SMART) provides information related to health of the hard drive based on certain attributes of the hard disk drive. The SMART monitoring system evaluates the health based on attributes such as reported un-correctable errors, un-correctable sector count, reallocated sector count etc. Using these attributes and changing values provided by the monitoring system we can determine if a hard disk is expecting imminent failure. While many of these SMART attributes have been standardized between hard disk manufactures, some of these remain vendor specific. Many disks do not report all SMART attributes. Multiple research studies focusing on predicting hard disk failures use this dataset but limit their study to homogenous disk populations. In reality, a datacenter will have composition of disks with variety of make and model. We used Backblaze Drive Stats dataset

(Q1 2021) to train and validate our implementations as they provide daily SMART data snapshot for disk of various make and model collected from their datacenter.

Long short-term memory (LSTM) is an artificial neural network with feedback connections. LSTM networks are pertinent to prediction and classification problems based on time series data. A LSTM unit is more sophisticated form of recurrent neural network (RNN) [29] composed of gates (input gate, output gate and forget gate). These gates memorize and regulates the flow of data in and out of the cell. LSTMs have an advantage over recurrent neural networks as it is insensitive to gap length. Bi-directional long short-term memory (BI-LSTM) is an extension of LSTM wherein sequence information is processed in both directions – past to future and vice-versa. LSTM preserves information only in one direction. Bi-directional LSTM puts two independent sequence information together. This allows the flow of information in both forward and backward direction at every time step. Since, input flows in both forward and backward direction in Bi-directional LSTM – it can understand context better than vanilla LSTM.

1.2. Problem Statement

Identifying SMART data attributes among heterogenous population of disks to predict imminent disk failure and using these parameters to build a bi-directional LSTM based model to predict disk failure within reasonable time frame.

1.3. Aim and Objectives

This research is aimed at identifying generic SMART data attributes among heterogenous population of disks. Using these generic attributes, we will then propose a model based on bi-directional LSTM to predict disk failure with accuracy at par with industry standards.

The objectives of this research are based on the aim of this study. They are:

1. To identify generic SMART data-based parameter among heterogenous disk population.
2. Using these generic parameters, build a bi-directional LSTM based model to predict disk failures.
3. Optimize the model for increasing failure detection rate (FDR) and reducing false alarm rate (FAR).
4. To evaluate the model against classic LSTM model.

1.4. Scope of the Study

Many studies have been conducted attempting to apply machine learning technique to predict hard disk failures as it has been a hot topic, both in academia and in the industry. In this research, we will limit our study to predictable disk failure. Hard drives have built-in system to report array of statistics regarding its health. For our research, we have used Backblaze dataset (Q1 ,2021) that is available publicly to train and validate our model.

An effective disk failure prediction model should give high failure detection rate while giving low false alarm rate. Since hard disk manufacturers do not agree on the definitions of some SMART attributes, we are limited by the attributes that have been standardized. For some make and model, SMART attribute values are largely unreported and do not yield any meaningful data for predictive analysis.

The SMART attributes dataset is largely imbalanced as the number of healthy disks vastly outnumber the failed disks. Extremely imbalance data makes prediction very difficult and may mislead experimental results. To address this issue, we have used oversampling technique.

1.5. Significance of the study

Data storage demands are increasing exponentially in this digital age. Data storage is vital for successful organizations. Electronic data storage allows for convenient backup and secure vital data. Organizations are increasingly making data-driven business decisions. Data analytics gives organisation a competitive edge over its competitors in today’s fast-paced industry. To increase the quality of such business-critical decisions, organizations need to store, process and analyse large amount of data. Datacenters with large computing infrastructure facility & storage system are leveraged for such analytics.

Hard disk, also called hard disk drive is a magnetic storage medium used to store data in electronic form. Hard disk drives are primarily evaluated based on its capacity and its performance. Recent advancements have made hard disks more reliable, affordable & less prone to mechanical issues. While the market share of SSDs (Solid State Drives) is increasing, HDDs still dominate in meeting datacenters storage requirements. Capacity planning & inventory management of hard disks in datacenters is an operational challenge.

Hard disk drive is the most vulnerable component in a datacenter. They do eventually failure due to regular use. These failures can cause loss of data or degraded customer experience. Using modern technology, it is possible to predict and plan to mitigate such failure. Prudent planning using these predictive analytics can turn catastrophic storage failure incidents into planned datacenter maintenance events.

The main objective of this study is to find a methodology for disk failure prediction using Bi-directional LSTM in heterogenous environments – as most other studies focus on homogenous population of disks. In practical scenario, large datacenters rarely have all disks of same make and model in use. We will compare our model with previously studied disk failure prediction models based on accuracy and false alarm rate.

1.6. Structure of the study

This structure of this study is multi-phase. We started with undertaking a thorough review of related works and literature study (Chapter 2). Reviewing related work helped us putting this study into perspective. It provided guidance on possible approaches and challenges that we may encounter during the course of this research. Literature Study helped us in identifying the scope of improvement in failure prediction among heterogenous population of disks. We discuss step by step approach to meet the research goals established (Chapter 3). We proceed to provide the details of implementation (Chapter 4). We analyse and discuss the results (Chapter 5) before we conclude our study with the contributions and provide recommendation to improve the prediction model in future studies. (Chapter 6).

CHAPTER 2: LITERATURE REVIEW

2.1. Introduction

Datacenters have to plan for efficient replacement of unhealthy hard disks to optimize cost of operations and remain competitive. SMART data can give us insights on the condition of the hard disk drive. This data collected over a time gives us the ability to predict disk failures based on the status of SMART data. Proactively predicting disk failures helps with lower recovery time and better performance in datacenters.

2.2. Disk failure prediction using RNN models

Multiple attempts have been made to implement neural network-based approach to identify failing disks. We will look at the related work done in the following section. We will also look at different models of RNN. Recurrent neural networks are classified under artificial neural networks. They may be directed or undirected graph. Application of RNN includes speech recognition, hand-writing recognition. RNN can be used to process variable sequence of input data.

(Ganguly et al., 2016) proposed a two-stage ensemble model using different machine learning and statistical modelling techniques for cloud platform. A combination of SMART data and windows performance counters was used to enhance prediction accuracy. In stage 1, decision tree is used to get first few powerful separation slices which are effective in identifying end-of-life disks. In stage 2, logistic regression model is used to choose cut off probability of disks that fell in low purity leaf in Stage 1. The study is formulated on homogeneous disks and relies on collection of performance counters.

(Wang et al., 2014) suggested the use of two-step parametric method to predict impending failure of HDDs using the aggregate of statistical models. The two steps involved in this approach are: anomaly detection and failure prediction. In the first step, Mahalanobis distance is used to aggregate all monitored variables and transformed into Gaussian variables by Box-Cox transformation. Mahalanobis distance is the distance between point P and distribution D. It’s used to calculate how many standard deviations P is away from the mean value of D. In the second step, a sliding window-based test is used to track anomaly progression. The disk is marked to fail if the occurrence of anomalies in the time frame is found to be statistically significant.

A Decision tree is a tree structure, with each internal node representing a test on an attribute, each branch representing a test outcome, and each leaf node (terminal node) holding a class label.(Rincón et al., n.d.) addressed the case of datacenters with heterogeneous disk populations and proposed to build global disk failure predictors that would apply to all makes and models. To identify the strongest disk failure indicators, reverse arrangement test was applied to SMART attributes. The study investigated three different machine learning models – of which decision tree model proved to be the best model. The decision tree-based model identifies 52% of all disk failures.

Most supervised machine learning algorithms rely on annotated datasets for training. A training set is used in supervised learning to instruct models to produce the desired results. This training dataset has both the right inputs and outputs, enabling the model to develop over time. The loss function serves as a gauge for the algorithm's correctness, and iterations are made until the error is sufficiently reduced. SMART attribute datasets are however highly imbalanced due negative samples (healthy disks) highly outnumbering positive sample (failed disks). (Jiang et al., 2019) proposed a novel semi-supervised for lifelong disk failure training using generative adversarial network. A 2D image representation technique is discussed to enable automatic feature extraction. The GAN-based model is trained only healthy disks hence avoiding the limitations of data imbalance.

In their analysis (Franklin, 2017) based on empirical observation that reallocated sector count increases significantly prior to disk failure, identified that high reallocated sector count can be used as a pre-failure indicator of unhealthy disks. Since reallocated sector count can be monitored in real-time (Franklin, 2017) proposed to proactively replace disks based on this condition-based monitoring. (Strom et al., 2007) discussed a reliability model for the hard disk drive focused on head-disk separation. Under this model, the head-media separation characterized as function of temperature, altitude, humidity and operating mode. The model’s capability to quantitatively evaluate the impact of head-media separation, also called as clearance, helps in determining the possibility of disk failure.

LSTM is classified as a variant of recurrent neural network. LSTM networks have a feedback loop which can process multiple sequence of input with delay. The first layer is input layer. The LSTM consists of node that is made up of cells. The cells can retain values over varying time interval. The cell contains: input gate, forget gate and output gate. In practice, LSTM is used instead of RNN because it is more computationally effective and doesn't have the vanishing gradient problem.

(Yang et al., 2020) proposed a disk failure prediction system based on LSTM wherein the disk is classified as normal or doomed to fail within 5 days. Using LSTM, the SMART data is trained to classify the disk either as normal or to fail within 5 days. The proposed model achieved 94.5% Failure Detection Rate and 0.7% False Alarm Rate. The study identified two important parameters: *sample_days* and *predict_failure_days*. *sample_days* is the time window of input data considered for training the model. To avoid old data from misleading the trained model this parameter is kept reasonably small to increase the accuracy of prediction. The other parameter, *predict_failure_days* is number of days before the predicted disk failure event occurs. *predict_failure_days* parameter is used to define the alarm boundary. The study compares various algorithm and the effects of varying the *sample_days* attribute. Missing values are padded as SMART data occasionally have acquisition failures or errors during transmitting data. The dataset is normalized using interval scaling method. As in the case of most SMART datasets, the number of positive samples (failed disk) in ZTE's SMART dataset is far less than number of negative samples (healthy disks). To counter this, this paper used four methods of sample balancing to balance the data and improve FDR i.e., ADASYN, SMOTE, ADASYN with ENN and SMOTE with ENN. Among these, SMOTE combined with ENN improved the performance the most and hence was used for data balancing. This paper tired common algorithms such as RNN, random forest, SVM, LOG, decision tree and AdaBoost before settling on LSTM as it is an improved version of RNN which can handle vanishing gradient problem. The paper attempted to solve the problem of model aging and provides a way to widen the range of prediction window.
(Zhang, 2019) used a combination of XGBoost, LSTM and ensemble learning algorithm to predict disk faults within 42 days with 78% accuracy.(Dos Santos Lima et al., 2017) presented an approach to estimate remaining useful life (RUL) based on SMART parameters capable of predicting failures both in short and long-term intervals. Custom spaced binning of RUL is applied instead of evenly spaced intervals as custom spaced binning over provides

finer control of the prediction. Once the RUL binning is complete, LSTM's many-to-many architecture is used to tackle disk failure prediction as multi-label classification problem. In contrast to most existing studies, which tackles disk failure prediction as classification problem (Anantharaman et al., 2018) discussed a way to predict remaining useful life (RUL) using random forest and LSTM.

(Lima et al., 2021) proposed a method for predicting health degree of hard disks using deep neural networks. Using new encoding for the class labels as opposed to traditional binary classification, the model classifies the disk's health to its nearest health level. Classifying the health of hard disk far from its true health state is penalized more that when the disk is classified closer to its true health state.

For training most models, the dataset needs to be clearly labelled. (Healthy or failure). In some cases, HDD failures can occur abruptly. In such cases, SMART data may not be available.
(A multi-instance LSTM network for failure detection of hard disk drives, 2020) proposed a multi-instance long term sequence classification model based on LSTM to tackle such scenarios. The SMART data maybe be unavailable during failure, and in turn make the data imbalanced. To deal with the data imbalance problem, degradation characteristics learnt using long-term data is studied and used to predict disk failure.

(Suchatpong and Bhumkittipich, 2014) introduced failure prediction using decision tree learning with the intention to eliminate the simulation of various environments and to reduce process analysis time for disk manufacturers. C5.0 algorithm is used as multi-classifier for classification of disk failure modes.

(Wang et al., 2021) proposed a multi-instance method to detect anomalies based on attention mechanism. Since failure data during degrading period is sparse, data is highly imbalanced. In order to find hidden fault information, a multi-instance long term data classification method based on LSTM and attention mechanism is used.

(Li et al., 2018) discussed two new metrics that go beyond traditional metrics i.e., FAR to evaluate the model: migration rate and mis-migration rate. MR and MMR are used to determine the quality of failure prediction. MR measures how much at-risk data is migrated as a result of correct prediction. MMR measures how much data is migrated due to incorrect prediction.

(Li et al., 2014) proposed a health degree model based on regression tree which provides disk's health status rather than a simple classification result. Warnings raised by the prediction model can be dealt in the order of disk's health status. However, these health degree-based models do not outperform binary classification models.
(Dos Santos Lima et al., 2018) conducted a comparative study to evaluate the performance of recurrent neural models and assessed the impact of initialization techniques. The study found that among the deep models, LSTM had the best performance.

Misclassification of disks based on faulty model may cause unnecessary migration overhead or worse, loss of data.(Zhang et al., 2022) proposed a cost-sensitive learning engine (CSLE) using a two-phase feature selection based on Cohen's D and genetic algorithm to minimize the misclassification cost.

While most approaches treat the task of predicting disk failures as static – training and testing on fixed set (Zufle et al., 2021) compared various updating strategies to account for aging and changes in failure patterns. In addition to SMART data, (Xu et al., 2022) used disk loss characteristics, disk performance status and system log to design a disk failure prediction model based on LSTM.

2.3. Summary

In this chapter, we studied various related work and studied conducted in the field of predicting hard drive failures. From literature review, we see that there are multiple ways the problem can be approached. We found that most studies focus on homogenous population of disk due to lack of standardization among hard drive manufacturers. From the related work done previously, we can understand the challenges that exists and help us in identifying the opportunities available for improvement. The literature review showed the limitations in existing models and helped in deriving an evaluation criterion for our model. Chapter 3, will explore how we will approach in identifying the right set of parameters that are generic to all make and model of disks and build a Bi-LSTM based hard drive failure prediction model.

CHAPTER 3: RESEARCH METHODOLOGY

3.1. Introduction

In this chapter, we will discuss dataset and research methodology taken to meet the research goals. We will discuss overview of the plan to compare performance of different RNN models. The research will apply one of the deep learning models for prediction of disk failure and compare its performance with other RNN models that have been previously studied.

3.2. Research Design

In this research we aim to study the performance of Bi-directional LSTM on heterogenous population of disk. For this case, we require the right dataset consisting of labelled data for disk health for variety of make and model from a reliable source.

We source our data from backblaze dataset [27] which is published on quaterly basis. Jupyter notebook was setup on the remote virtual machine with data analytical packages required to process and analyse the dataset. We proceed to analyse the dataset to better understand its intricacies. TensorFlow and Keras libraries are used for implementation. We will analyse the result from following 4 different instances of disk failure prediction models:

1) LSTM – on homogenous population of disks
2) Bi-LSTM – on homogenous population of disks
3) LSTM – on heterogenous population of disks
4) Bi-LSTM – on heterogenous population of disks (Primary Model)

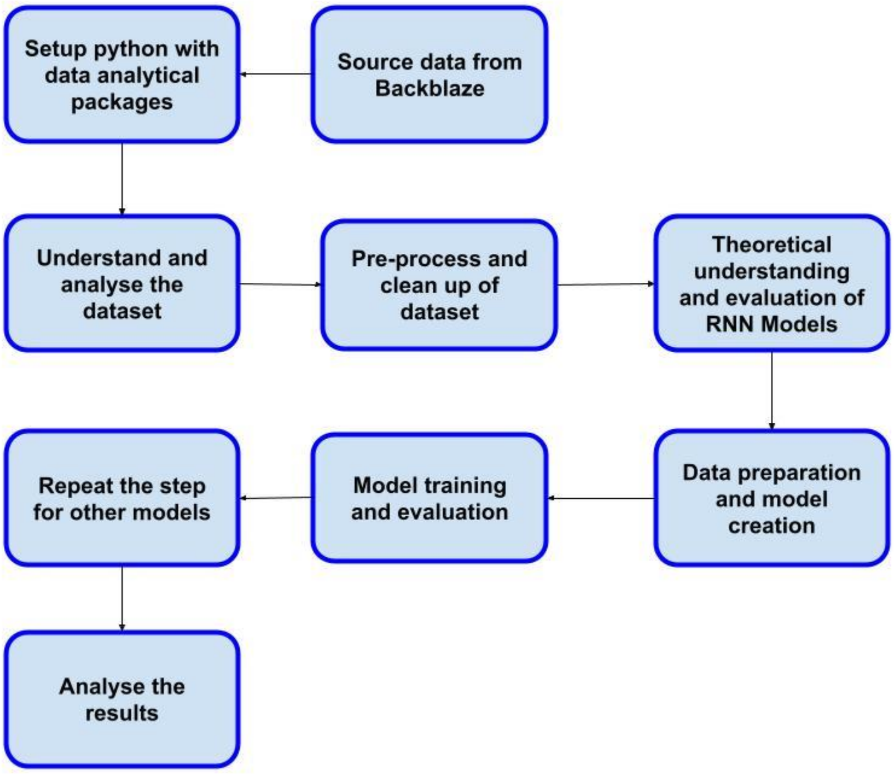

Figure 2. Research methodology workflow

3.3. Data Collection

Backblaze publishes insights and statistics based on the data collected from their Datacenter since 2013, on quaterly basis. The dataset is free to use for research purposes. The dataset fits our use case, as it contains labelled data for heterogenous populations of disks. We will train, test and evaluate our model using data published by backblaze for the period of 01 Jan, 2021 – 31 March, 2021 (Q1, 2021).

The schema for dataset may change quarter to quarter as more SMART parameters maybe reported. For the selected period (Q1, 2021), we have 144 SMART parameters in the dataset. Out of these 144 smart attributes, half of the attributes are raw values (vendor specific range) and rest of them are normalized. Not all SMART attributes are reported by certain models. Certain attributes maybe reported sparsely, hence the dataset has lot of missing values. Selected attributes for the study and its description is provided in Table 1. We will drop the vendor specific raw values as they may mislead our model. As in the case of most SMART datasets, negative samples vastly outnumber the cases of positive samples. We will use over sampling and under sampling technique to deal with imbalanced dataset. From the dataset 60% of entries will be used to train the model while 40% of entries will be used to test and evaluate the model.

3.4. SMART Attributes

Most modern hard disks are capable of reporting its health status with the help of Self-Monitoring, Analysis and reporting technology (SMART). SMART offers a signalling method for internal electromechanical sensors of a disk to report disk's health status to host system. SMART consistently monitors various parameters associated with disk's health status such as read write errors, throughput, bad sectors reallocated, un-correctable errors, temperature, power on hours, vibration levels etc. Using values reported by the SMART monitoring system we can determine if a hard disk is expecting failure in near future.

It should be noted that during catastrophic, SMART data maybe be inaccessible. In such cases, the SMART data values may not be captured. Drives with SMART capability may maintain error logs. These error logs provide additional insight if the problems are disk related or otherwise. Some operation systems such as Microsoft Windows provide support for SMART data natively. Plenty of free and third-party software exist, that provide detailed information and real-time warning related to unhealthy disks. SMART monitoring may result in degraded performance of the host system which is why it disabled by default on most consumer-standard motherboards.

Lack of hardware and software standards for SMART data exchange is a major limitation. Hard drive manufacturers define set of attributes and threshold values that shouldn't be breached under normal operations. Although some agreement exists among major hard drive manufacturers, some SMART attributes are still highly vendor specific. Vendor may have their own implementation and range of values for certain SMART attributes. The count of SMART attributes monitored and reported may vary with manufacturer to manufacturer.

Depending on the interface, certain motherboards and software may not be able to communicate with certain SMART capable drives. RAID is storage virtualization solution that combines multiple physical drives into one or more logical units for data redundancy.

Data is distributed across disks based on raid levels that are configured depending on required level of performance and redundancy. Many software programs designed to analyse changes in drive behaviour and relay SMART alerts to the host system do not function when the system is configured for RAID support, typically because the RAID array subsystem does not allow the host to directly access individual physical drives under normal RAID array operational conditions.

Smart ID	Attribute name	Description
1	Read Error Rate	Indicates the rate of hardware read errors that occurred when reading data from a disk surface
3	Spin-Up Time	Average time of spindle spin up
4	Start/Stop Count	A tally of spindle start/stop cycles
5	Reallocated Sectors Count	Count of reallocated sectors
7	Seek Error Rate	Rate of seek errors of the magnetic heads
9	Power-On Hours (POH)	Count of hours in power-on state
10	Spin Retry Count	Count of retry of spin start attempts
12	Device Power Cycle Count	This attribute indicates the count of full hard disk power on/off cycles.
190	Temperature Difference from 100	Value is equal to (100 -temp °C), allowing manufacturer to set a minimum threshold which corresponds to a maximum temperature
192	Power-off Retract Count	Number of times the heads are loaded off the media
193	Load/Unload Cycle	Count of load/unload cycles into head landing zone position.
194	Temperature	Current internal temperature
197	Current Pending Sector Count	Number of "unstable" sectors (waiting to be remapped). If the unstable sector is subsequently written or read successfully, this value is decreased and the sector is not remapped
198	Uncorrectable Sector Count	The total number of uncorrectable errors when reading/writing a sector
199	UltraDMA CRC Error Count	The number of errors in data transfer via the interface cable as determined by ICRC (Interface Cyclic Redundancy Check).
240	Head Flying Hours	Time while head is positioning

Table 1. Description of selected SMART Attributes [30]

3.5. Recurrent Neural Network

Artificial neural networks (ANN) are inspired from the design of biological neural network. Neural networks consist of nodes through which signals are passed. These nodes have typically weight assigned that varies as the learning proceeds. Recurrent neural network (RNN) is a subset of artificial neural network where connections between nodes can create a cyclic path to process sequential data. Recurrent neural networks are used in sequence models such text streams, video streams, audio streams, time-series data etc. RNNs can store and memorize and store previous results, which is great for solving sequential data problems. However, RNNs has its own limitations as the training is complicated and the computation time is high.

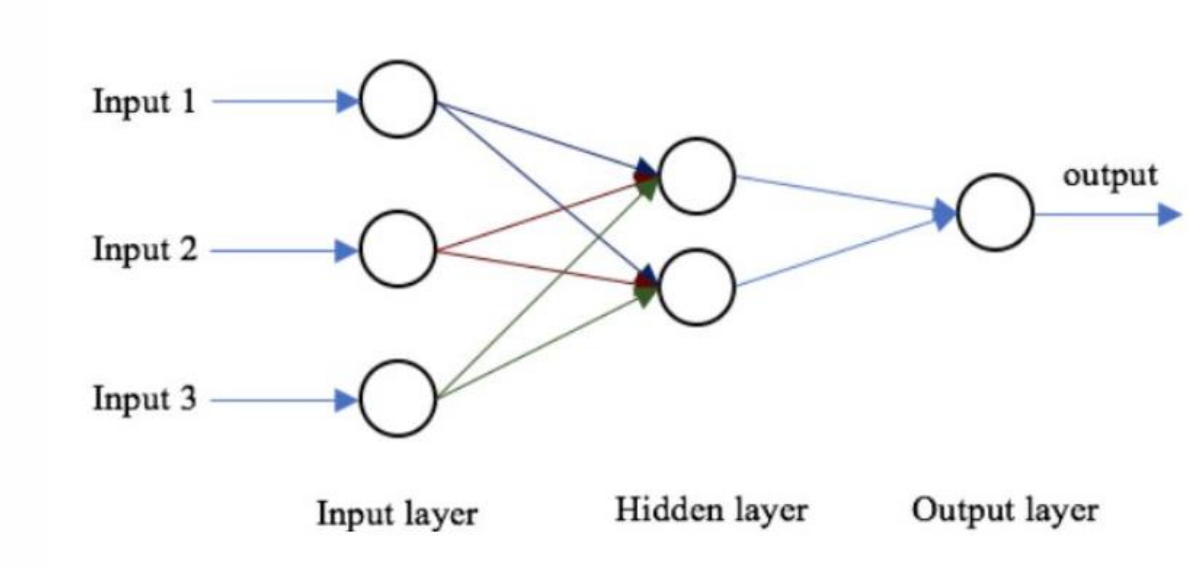

Figure 3. Traditional RNN model and its layers

RNN are good from solving problem with sequential data but suffer from short-term memory. The vanishing gradient problem refers to the problem where gradients of the loss function for certain activation functions approaches zero as more layers are added. The problem makes it harder to train neural networks as the networks learn at a very slow pace or in some case does not learn at all. Sigmoid function is a log function with characteristic ‘S’ shape. Sigmoid function output values in the range of (0,1) used in binary classification problems.

3.5.1 Long short-term memory (LSTM)

LSTM is subset if recurrent neural networks used to build and train sequential data models. LSTM are capable of learning long term-dependencies. Apart from single data points, LSTMs are capable of processing entire sequence of data as it has feedback connections. LSTMs exhibits excellent performance on large variety of machine learning problems. Some of the applications are in the field of speech recognition, time series data analysis, machine translation etc.

A memory cell plays the central role in an LSTM model, known as the cell state. The information that passes through the memory cell is regulated by gates. A sigmoid neural net layers assists the mechanism to decide if the information should pass through the memory cell. Each cell acts as recurrent network on its own. LSTMs are capable of capturing long term temporal dependencies effectively without much modifications.

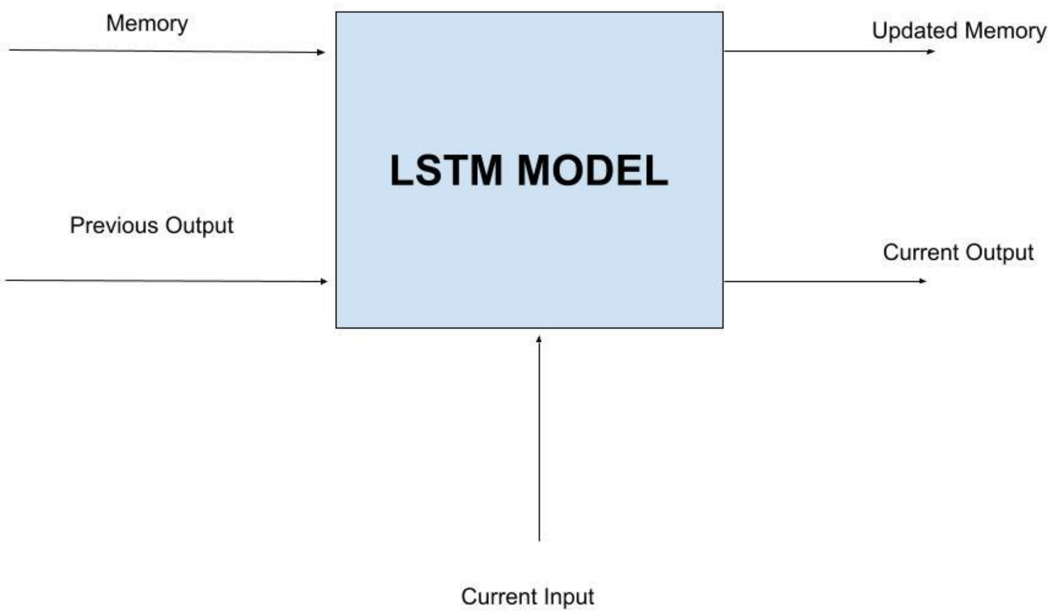

Figure 4. LSTM Model

LSTM uses gates to control the flow of information from sequential data. These gates act as filters which decide if the past learnings should be passed along to future. The forget gate decides what information should be retained. Information is passed through a sigmoid function to output a value between 0 to 1. While, value closer to 0 means the cell should forget the information, values closer to 1 mean the cell should retain the information.
To update the cell state, input gate is used. The current input and previous hidden state is passed onto a sigmoid function. This output of sigmoid function decides if the input is important or not important. The output gate decides the fate of next hidden state. The new cell state and the hidden state is carried over the next time-stamp.

The output for LSTM depends on the following three things:

1) The input data at current time stamp
2) The previous hidden state – gathered at a previous point in time
3) The current cell state

3.5.2 Bi-directional long short-term memory (Bi-LSTM)

Bi-directional LSTMs are upgraded version of classic LSTM. Bi-directional LSTM have complete information about the sequential data at any given point of time.

As seen in figure 5, Bi-directional LSTM have the sequence information in both forward (past to future) and backward (future to past). While conventional RNNs and LSTM are capable of only using previously gathered context to process the data in one-direction, bi-directional LSTMs are capable of processing data in both directions. Bi-directional LSTM perform slightly better over classic LSTM but take more time to train the model as training the model needs to be performed in both directions.

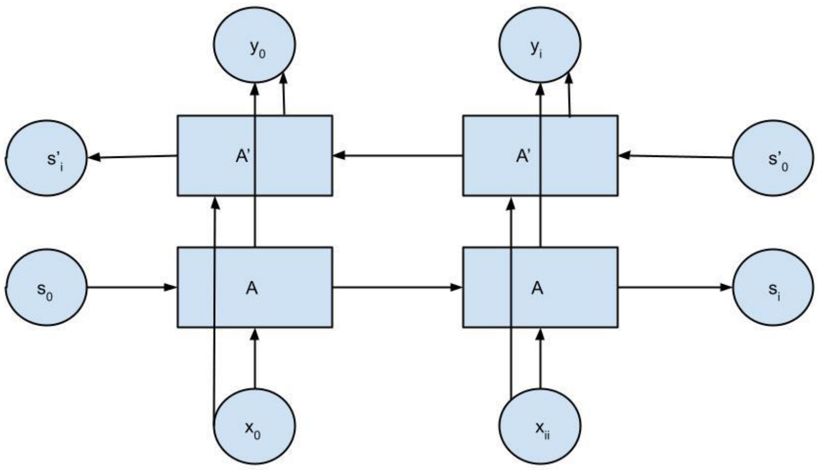

Figure 5. Bi-LSTM Model

3.5.3 Gated recurrent unit (GRU)

Gated recurrent units (GRUs) are a form of recurrent neural networks with gating mechanism similar to that of LSTM. The performance of GRU is similar to that of LSTM but has fewer parameters. The basic difference between GRU and LSTM is that GRU lacks an output gate. In certain cases of smaller and less frequent datasets, GRU can even perform better that LSTM.

Gated recurrent units consists of following gates:

1) Update Gate
2) Reset Gate
3) Current memory Gate

Update gates determines how much of the learnings from past sequential data needs to be passed along into the future. The reset gate determines how much of the learnings from the past sequential data needs to be forgotten. Current memory gate is used introduce non-linearity during model training.

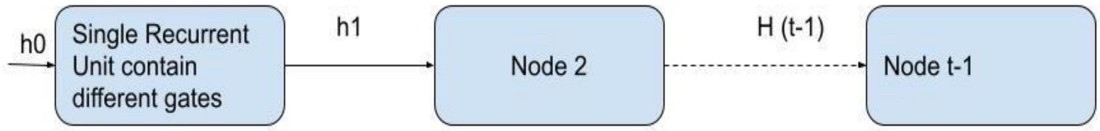

Figure 6. Gated Recurrent Unit

Fig 6. show the working of gated recurrent unit. Here, h stands for hidden state. The current input and hidden state are modulated by the gates in the network.

3.6. System Setup

Data preparation, training, testing and evaluation of the model was done on a virtual machine hosted on linode [34], a cloud hosting platform. Data clean-up and exploratory data analysis were performed on a 16-core virtual machine with 300GB RAM running ubuntu operating system. Since the dataset was large (4.94 GB) with approximately 15.28 million records, the model was trained on a virtual machine with high-end configuration hosted on linode.

The dataset was downloaded to the virtual machine directly using curl command. Jupyter notebook was installed on this machine as setting up python with data analytical packages was a requirement for this study. Details of the system is given in table 2. The setup allowed browser-based remote access to deploy and execute code. The notebooks are accessed via browser on a laptop (MacBook Pro – Intel Core i7 – 2.6Ghz).

System Requirements	
CPU	16 Core
Memory (RAM)	300 GB
HDD	340 GB
Operating System	Ubuntu 22

Table 2.System Requirements

3.6.1. Pandas

Pandas is a python package used for fast and flexible analysis of data. Pandas provides various functions to perform data manipulation on large scale observational / statistical datasets. Pandas helps to perform effective exploratory data analysis – allowing to perform various data cleaning, reshaping and merging operations. Pandas package is well suited for tabular data (heterogeneously-typed columns) and ordered/unordered time series data.

3.6.2. TensorFlow and Keras

TensorFlow is an open-source machine learning python library. It has comprehensive ecosystem of libraries and tools required for implementing the model. TensorFlow helps implementation by executing low-level tensor operation on GPUs/CPUs. TensorFlow is capable of scaling to multiple devices/clusters for problems with intensive computation requirements.

Keras is simple, flexible and powerful high-level API written in python used in implementation of deep learning models, which runs on top of the machine learning platform – TensorFlow. Keras empowers researchers to perform fast experimentation. Keras offers industry-level performance and scalability.

CHAPTER 4: IMPLEMENTATION

4.1. Introduction

Chapter 3 provided an overview on the methodology that will be used to build the model. We discuss about pre-processing the dataset and performing exploratory data analysis. This chapter will cover implementation which includes performing operations on the dataset to ensure the data is in right format for model training. The implementation of the model is done using TensorFlow and Keras library.

4.2 Understanding the Dataset

The dataset has close to 15.28 million records from January 01, 2021 to March 31, 2021. (Q1, 2021). The dataset comprises snapshots of drive statistics from backblaze datacenters on daily basis. The size of combined CSV files was approximately 4.94 GB.

The first 4 columns of the dataset are consistent for all years:

Attributes	Description
Date	date (yyyy-mm-dd)
Serial Number	manufacturer-assigned serial number
Model	manufacturer-assigned model number
Capacity	drive capacity in bytes

Table 3.Attributes

The rest of the dataset contains raw and normalized smart attributes data. It should be noted that there cannot be more than 255 pair of SMART attributes reported.To train, test and evaluate our model we used data from Q1, 2021 – consisting of 144 smart attributes. Out of these 144 smart attributes, half of the attributes are raw values (Vendor specific range) and rest of them are normalized. We drop the vendor specific raw values as they may mislead our model.

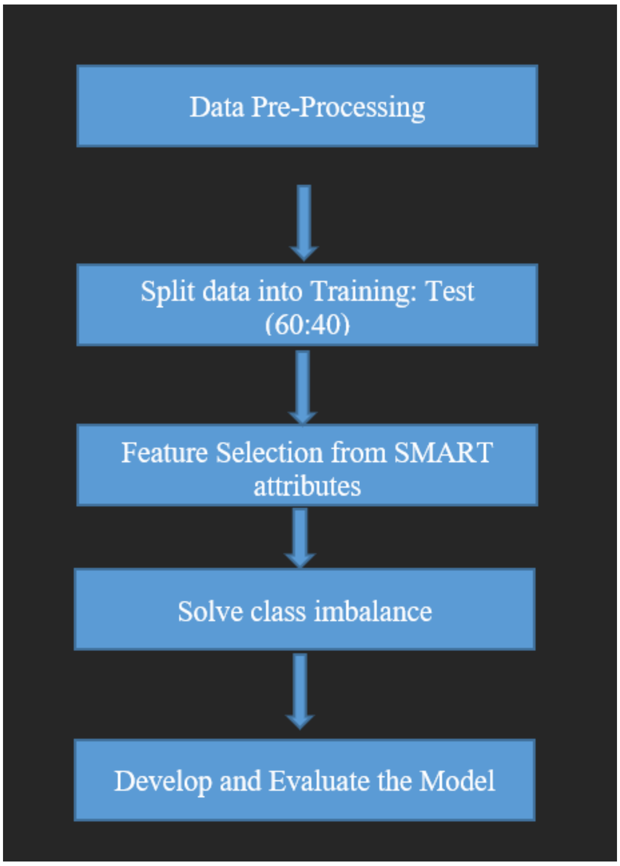

Figure 7. Flow Chart - Building the Model

To prime the dataset for model building we will perform data-pre-processing. In the first step, the raw values that are vendor specific will be dropped from the dataset. In next step, we look at the percentage of missing values for SMART attributes. The details regarding percentage of missing values for Q1, 2021 dataset are tabulated in Table 3.5.1.

SMART Attribute	**Percentage of missing values**
smart_1_normalized	0.136616
smart_2_normalized	60.115231
smart_3_normalized	0.884835
smart_4_normalized	0.884835
smart_5_normalized	0.829646
smart_7_normalized	0.884835
smart_8_normalized	60.115231
smart_9_normalized	0.136623

smart_10_normalized	0.884835
smart_11_normalized	99.580647
smart_12_normalized	0.136623
smart_13_normalized	99.944811
smart_15_normalized	100
smart_16_normalized	99.306977
smart_17_normalized	99.306977
smart_18_normalized	79.050735
smart_22_normalized	85.2289
smart_23_normalized	85.014494
smart_24_normalized	85.014494
smart_168_normalized	99.306977
smart_170_normalized	99.305302
smart_173_normalized	99.304354
smart_174_normalized	99.304354
smart_175_normalized	99.997377
smart_177_normalized	99.306977
smart_179_normalized	99.944811
smart_180_normalized	99.944811
smart_181_normalized	99.944811
smart_182_normalized	99.944811
smart_183_normalized	88.322009
smart_184_normalized	73.205375
smart_187_normalized	40.924254
smart_188_normalized	40.923306
smart_189_normalized	73.207998
smart_190_normalized	40.924254
smart_191_normalized	58.225691
smart_192_normalized	0.191812
smart_193_normalized	1.149537
smart_194_normalized	0.136623
smart_195_normalized	60.439682
smart_196_normalized	59.959632

smart_197_normalized	1.701411
smart_198_normalized	0.829646
smart_199_normalized	0.829646
smart_200_normalized	66.591727
smart_201_normalized	99.944811
smart_202_normalized	99.944811
smart_206_normalized	99.999052
smart_210_normalized	99.999052
smart_218_normalized	99.306977
smart_220_normalized	85.344401
smart_222_normalized	85.344401
smart_223_normalized	83.51875
smart_224_normalized	85.344401
smart_225_normalized	99.735298
smart_226_normalized	85.344401
smart_231_normalized	99.306977
smart_232_normalized	99.306977
smart_233_normalized	99.251788
smart_234_normalized	99.998325
smart_235_normalized	99.304354
smart_240_normalized	26.227634
smart_241_normalized	37.843646
smart_242_normalized	37.844595
smart_245_normalized	99.944811
smart_247_normalized	99.999052
smart_248_normalized	99.999052
smart_250_normalized	100
smart_251_normalized	100
smart_252_normalized	100
smart_254_normalized	99.834667
smart_255_normalized	100

Table 4.Percentage of missing values by SMART attributes

One of the major issues we faced during our investigation was that large number of SMART attributes were missing for most make and model.

Once we determine the percentage of missing values, we drop the SMART attributes with more that 50 percent missing values as they are not useful for building our prediction model. For SMART attributes with less the 50 percent missing values we use mean imputation method. Mean imputation method involves computing mean of the observed variables and imputing missing variables with the computed mean value.

After we clean-up and solve the data imbalance in the dataset, we will use recursive feature elimination for feature selection process. We then build a bi-directional LSTM based model to train over 10 epochs using 60 percent of data as training dataset. We study the model's performance in comparison with classic LSTM's performance.

4.3. Univariate Analysis

In the next step, we calculate the count of disks per model.
To keep the model simple, we drop the models with counts less than 100000 from the dataset.

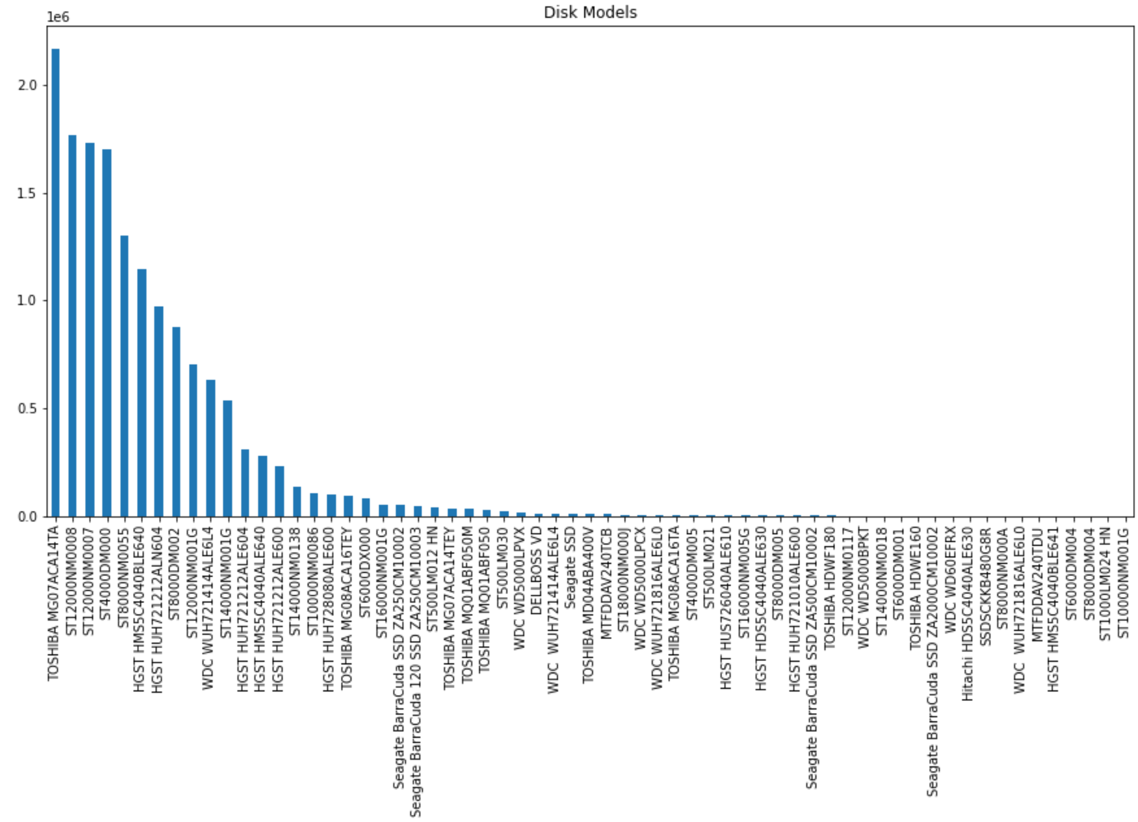

Figure 8.Count of disks by model (before pre-processing)

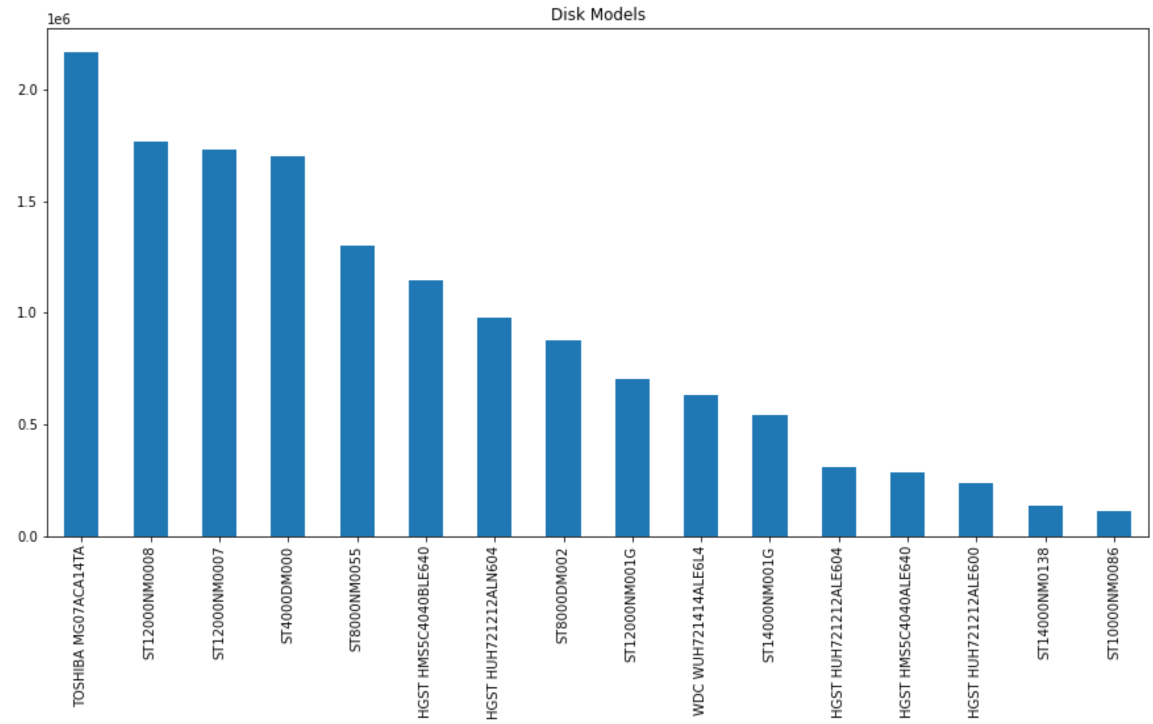

Figure 9.Count of disks by model (after pre-processing)

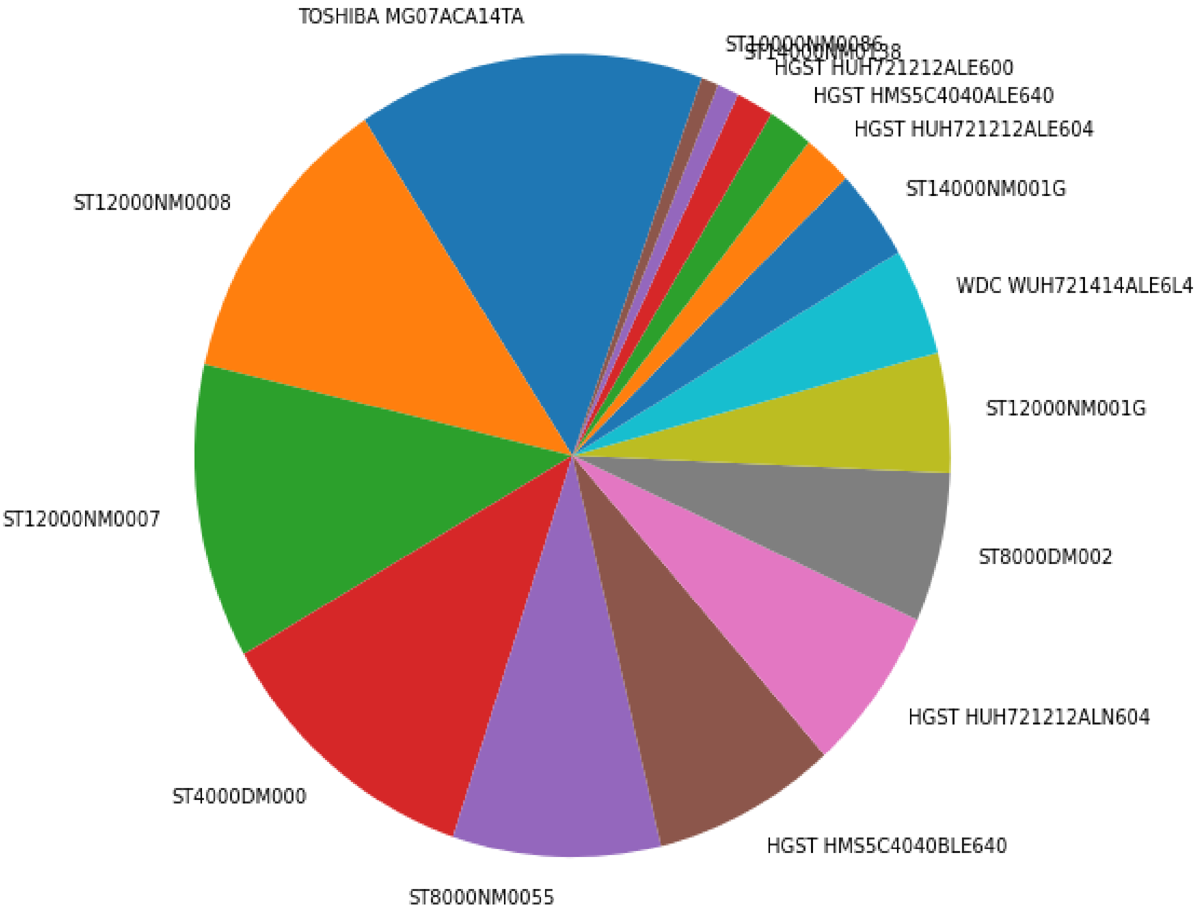

Figure 10. Disk Models

In figure 10., we plot a pie-chart of variety of disk models in the data. From Fig 4.2.1 we can clearly see that Segate disk models command more that half the total share of disks in the dataset. In Table 5, we list the count of disks by model number. This helps us better understand the mix of hetrogenous population of disks in the dataset.

In Table 6, we compare the count of healthy disks vs failed disks in the dataset. As we can see from Table 6, the dataset is highly imbalanced. While this is expected from the dataset as healthy disks vastly outnumber failed disks, it may be misled to train a model with imbalanced data. We will use up sampling technique to tackle the issue of data imbalance.

Disk Model	Count
TOSHIBA MG07ACA14TA	2165421
ST12000NM0008	1764318
ST12000NM0007	1732307
ST4000DM000	1701967
ST8000NM0055	1297674
HGST HMS5C4040BLE640	1146496
HGST HUH721212ALN604	974310
ST8000DM002	878106
ST12000NM001G	704446
WDC WUH721414ALE6L4	630260
ST14000NM001G	538401
HGST HUH721212ALE604	308793
HGST HMS5C4040ALE640	281692
HGST HUH721212ALE600	233948
ST14000NM0138	135157
ST10000NM0086	108057

Table 5. Count of disks by Disk Model

Disks	Count
Healthy	15286972
Failed	400

Table 6. Healthy vs Failed Disks

4.4. Multivariate analysis

In Figure 11., we analyse if certain SMART attributes can be better indicator of impending disk failure.

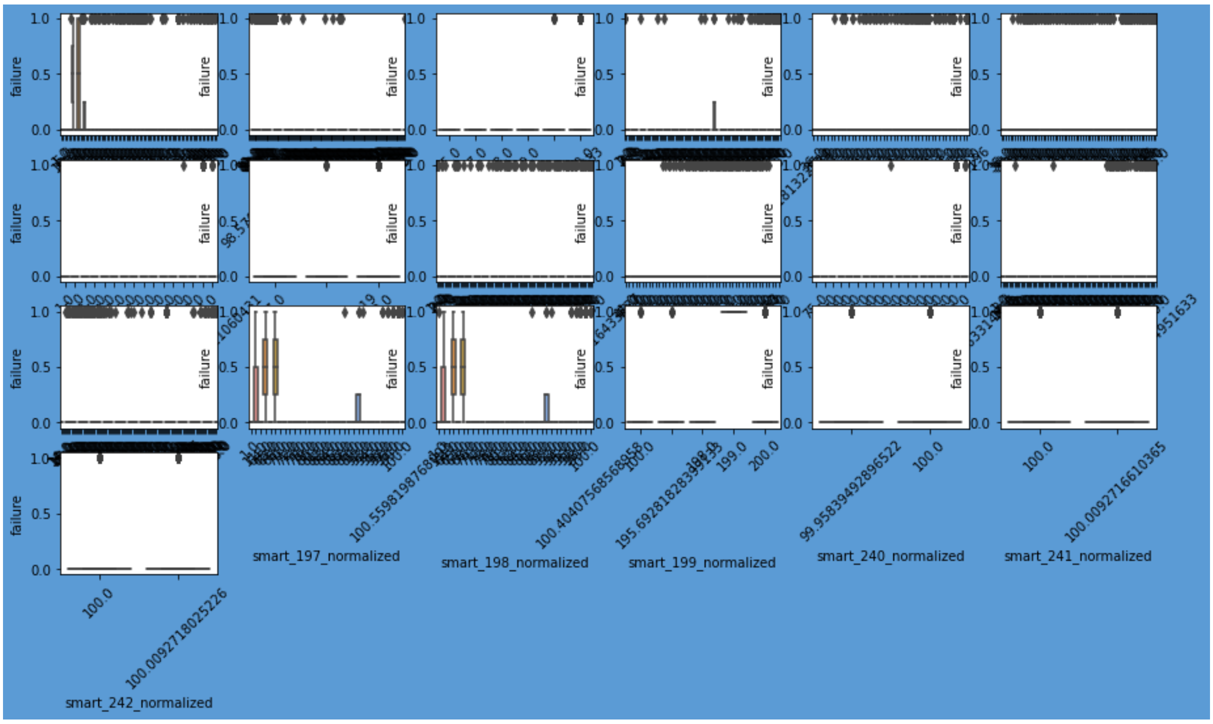

Figure 11. Selected SMART Attributes vs failure

4.5. Feature Selection

High intercorrelations among two or more independent variable can lead the model to have skewed and misleading results. This is widely known as multicollinearity problem. Existence of multicolinearity can lead to unreliable results. Multicollinearity can lead to wider confidence intervals which gives less reliable probabilities in term of the effects that an independent variable has on the model. To build a generalised model it is better to use independent variables that are not correlated.

The amount of multicollinearity can be measured using variance inflation factor in a set of regression variables. A high VIF value indicates that the independent variable is higly collinear with other variables in the model and needs to be eliminated. Typically, VIF < 5 is considered acceptable. VIF greater than 5 is considered as issue at it represents critical level of multicollinearity.

Variable1	Variable2	Correlation
smart_242_normalized	smart_241_normalized	1
smart_240_normalized	smart_194_normalized	0.841735
smart_242_normalized	smart_7_normalized	0.818428
smart_241_normalized	smart_7_normalized	0.818428
smart_241_normalized	smart_194_normalized	0.789254
smart_242_normalized	smart_194_normalized	0.789254
smart_194_normalized	smart_7_normalized	0.708251
smart_198_normalized	smart_197_normalized	0.675833
smart_242_normalized	smart_240_normalized	0.655465
smart_241_normalized	smart_240_normalized	0.655465

Table 7. VIF Calculation

Recursive feature elimination (RFE) is an effiecient way for feature selection from the give set of attributes. RFE is popular as it can be easily configure and is effective at selectiing features in the dataset that are most relevant in predicting the dependent variable. RFE is wrapper-style selection algorithm which internally uses filter-based feature selection.

Using RFE, the following smart attributes were found to be well-suited for the model (Table 7.).

Features selected using RFE
smart_1_normalized
smart_3_normalized
smart_7_normalized
smart_9_normalized
smart_10_normalized
smart_193_normalized
smart_194_normalized

Table 8. Feature selection using RFE

4.6. Bi-directional LSTM Model using TensorFlow

The model is complied using loss function “binary_crossentropy” as the problem is a binary classification problem. We use accuracy as the measure how good the model is in predicting drive failures. We use adam optimizer for our model. We trained the model using 100 neurons. The model is trained using training dataset for 10 epochs.The process was performed again for buiding a LSTM model with same dataset and similar conditions to compare the performance of both models.

The process was repeat couple of more time to perform similar experiments on homogenous population of disks. We chose “TOSHIBA MG07ACA14TA” for this purpose as it had the most value count (2165421) during the time frame specified.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 3, 16)             8000

 bidirectional (Bidirectiona  (None, 200)              93600
 l)

 dense (Dense)               (None, 1)                 201

=================================================================
Total params: 101,801
Trainable params: 101,801
Non-trainable params: 0
_________________________________________________________________
None
Epoch 1/10
183760/183760 [==============================] - 1098s 6ms/step - loss: 0.4108 - accuracy: 0.8049
Epoch 2/10
183760/183760 [==============================] - 1245s 7ms/step - loss: 0.4054 - accuracy: 0.8074
Epoch 3/10
183760/183760 [==============================] - 1248s 7ms/step - loss: 0.4053 - accuracy: 0.8075
Epoch 4/10
183760/183760 [==============================] - 1248s 7ms/step - loss: 0.4053 - accuracy: 0.8074
Epoch 5/10
183760/183760 [==============================] - 1255s 7ms/step - loss: 0.4053 - accuracy: 0.8075
Epoch 6/10
183760/183760 [==============================] - 1255s 7ms/step - loss: 0.4053 - accuracy: 0.8075
Epoch 7/10
183760/183760 [==============================] - 1257s 7ms/step - loss: 0.4053 - accuracy: 0.8075
Epoch 8/10
183760/183760 [==============================] - 1259s 7ms/step - loss: 0.4053 - accuracy: 0.8075
Epoch 9/10
183760/183760 [==============================] - 1260s 7ms/step - loss: 0.4053 - accuracy: 0.8075
Epoch 10/10
183760/183760 [==============================] - 1253s 7ms/step - loss: 0.4053 - accuracy: 0.8075
```

Figure 12. Bi-directional LSTM Model Summary (Heterogenous Population)

4.7. Summary

In this chapter, we covered how the data input was setup for the Bi-directional LSTM model.The model is trained over 10 epochs. To assess the model's performance, we also repeated similar setup for homogenous population of disks. We noticed that the accuracy and loss stay consistent after intial improvements. In the next chapter, we will analyse the results and compare these model's performance.

CHAPTER 5: RESULTS AND DISCUSSIONS

5.1. Introduction

In previous chapter, we explained how the model was setup to identify generic SMART attributes. The model was trained using Bi-directional LSTM and classic LSTM. We repeated the same process using homogenous population of disks for comparison.

5.2. Interpretation of results

It should be noted that the dataset was trained on 60 percent of dataset, while rest 40 percent was set aside for testing and evaluation of the model.

Model	Accuracy
LSTM on Heterogenous population of Disks	80.75%
Bi-LSTM on Heterogenous population of Disks	80.75%
LSTM on Homogenous population of Disks (TOSHIBA MG07ACA14TA)	50.01%
Bi-LSTM on Homogenous population of Disks (TOSHIBA MG07ACA14TA)	50.01%

Table 9. Training Results

The bi-directional LSTM (Heterogenous population of disks) model’s accuracy was plotted over the epoch, as seen in figure 14.

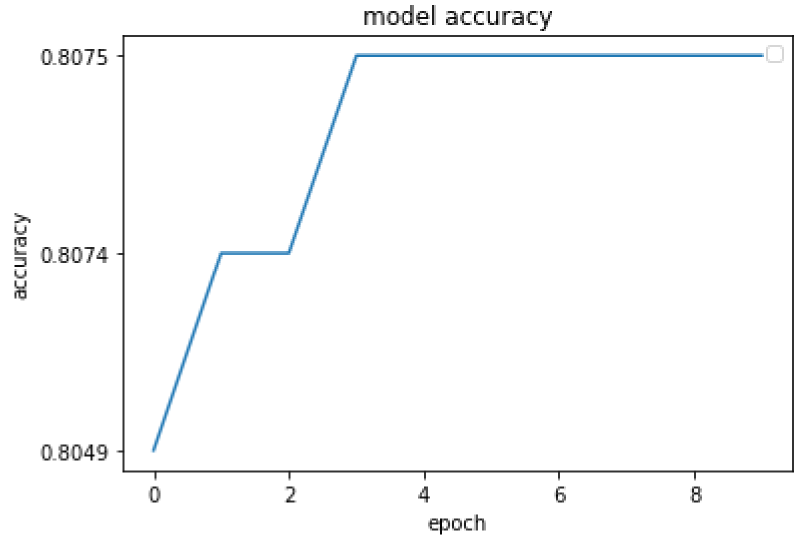

Figure 13. Model Accuracy

5.3. Sampling Method

As seen in Table 6., our dataset was imbalanced. Traditional model does not accurately evaluate the model's performance if the dataset is imbalanced. Traditional classification algorithms have a bias towards majority class. Resampling is a widely adopted technique for dealing with highly unbalanced dataset. The simplest way to implement over-sampling is to duplicate random samples from minority class. Similarly, the simplest way to implement under-sampling is to remove samples from majority class. Another technique that is widely used to tackle imbalanced data is called synthetic minority oversampling technique (SMOTE). We used up-sampling method to handle imbalanced dataset. Up-sampling minority class synthetically generates data points which are injected into the dataset. After performing this operation, the counts of both labels are similar. The procedure makes sure that the model does not incline towards the majority class.

5.4. Testing on Validation Dataset

We tested our models on test data (40% split from the dataset) and achieved the following results. It is to be noted that the test on homogenous population of disks was performed on the same dataset, but everything except the disk with largest value count was dropped. This in turn reduced the data samples for training by a huge margin. All other conditions were kept consistent.

Model	Accuracy
LSTM on Heterogenous population of Disks	80.67%
Bi-LSTM on Heterogenous population of Disks	80.74%
LSTM on Homogenous population of Disks (TOSHIBA MG07ACA14TA)	50.01%
Bi-LSTM on Homogenous population of Disks (TOSHIBA MG07ACA14TA)	50.01%

Table 10.Test Results

By varying the dataset size, we found that the margin of improvement Bi-LSTM provides over LSTM widen. We tested this by varying the dataset for 1 day, 10 days, 30 days and 100 days respectively.

5.5. Summary

In this chapter, we analysed the results from our model and compared its performance with LSTM. We also implemented the same model to analyse its performance over homogenous population of disks. Our model reported 80.74% accuracy which is a marginal improvement over LSTMs performance. We found that the margin of improvement widens as the size of dataset increases.

CHAPTER 6: CONCLUSIONS AND RECOMMENDATIONS

6.1. Introduction

In this chapter, we will conclude this research and discuss the contribution of this study. We will also provide recommendations for future research that will be undertaken in the field of predicting disk failures.

6.2. Discussion and Conclusion

We have taken part of the dataset to evaluate the model, therefore creating better generalized model. We have taken explicit care to avoid any overfitting of the data. We identified that the dataset is imbalanced and took appropriate steps to tackle the class imbalance problem. We used recursive feature selection to avoid multicollinearity problem. We found that the Bi-directional LSTM take more computation time but provides marginal improvements over classic LSTM.

6.3. Contribution to knowledge

This research identified generic parameters that can be used as base line across disk models and investigated the application of bi-directional LSTM on heterogenous population of disks. We found that the model achieved 80.74% accuracy which is marginally better than classic LSTM. We also found that this margin widens as the training dataset size increases, which is an expected behaviour. We also compared the models with homogenous population of disks with the same dataset. The performance of Bi-LSTM, again was found to be marginally better over classic LSTM.

6.4 Future Recommendations

Disk failure prediction is significant for reducing operational cost and proper inventory planning for a datacenter. Our model achieved 80.74% accuracy using limited SMART attributes that were available to us due to lack of standardization in the industry. Expanding on current work one can improve the model using additional data sources such a performance counters and error logs from the host system. In future, if there is consensus on the SMART attributes among manufacturers in the industry, prediction models can be improved as we will have wider range of standardized SMART attributes for training the model. Future work can also explore and study transformer deep-learning model as it allows for parallelization and therefore reducing training time. Another avenue that can be explored is to regroup disks by make and model and identity separate set of failure indicators for each set.

As a final note, the results of this study show that there is scope for improvement in the field of hard disk failure prediction. This should encourage the manufacturers and industry to attempt improving such solutions to achieve better results.

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APPENDIX I: RESEARCH PROPOSAL

HARD DISK DRIVE FAILURE PREDICTION USING RECURRENT NEURAL NETWORK

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Research Proposal

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Abstract

Technological advancements have improved the reliability and storage capacity for hard disk drives in the recent past. In the industry many critical applications are hosted onto the servers in datacenters specifically for the reliability and fault tolerance it provides. Even with the recent advancements in designing and manufacturing reliable hard disks, disk failures are inevitable due to wear and tear from handling large amounts of data over a course of time. Disk failures may cause degraded performance (due to worsening I/O operations) or complete loss of data which is undesirable. Disk failures can be classified as either predictable disk failures or unpredictable disk failures such as due accidents/natural calamity. For the purpose of this research, we will be focusing only on predictable disk failures. It is important to pre-emptively detect these predictable disk failures and provide warnings to replace bad disks to avoid longer I/O or data corruption. This will also help in inventory management of hard disks in the datacenter. We will explore the possibility of accurately identifying hard disk drives that may need replacement using recurrent neural network.

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1.Problem Statement

To predict hard disk drive failures in datacenter using improved recurrent neural network. We will also identify set of SMART attributes that increases the accuracy of our prediction.

2. Background

Datacenters are the backbone modern technology. Hard disks drives are probably the most important component of servers in the datacenters dealing with humongous volumes of data on daily basis. On an average hard disk lasts for 3-4 years before needing replacement. Disk failures are not an uncommon occurrence in a datacenter. It has been found that HDD failures account for 81.84% of failures in a datacenter(Wang et al., n.d.). We can plan and mitigate data loss using RAID implementations/mirror copies but we need to identify degraded disks to avoid service degradation/data corruption.

Disk failures can be classified into predictable and non-predictable failures. Predictable disk failure usually occurs due to regular wear and tear over time or frequent erasing attempts. Non-predictable disk failures occur due sudden power surge/Natural Calamities etc. While early replacement of disks can cause waste of disk life cycle, replacing it too late may cause data corruption/loss of data.

Self-Monitoring, Analysis and Reporting tool (S.M.A.R.T) provides information related to health of the hard drive based on certain attributes of the hard disk drive. The S.M.A.R.T monitoring system evaluates the health based on attributes such as reported un-correctable errors, un-correctable sector count, reallocated sector count etc. Using the attributes and values provided by the monitoring system we can determine if a hard disk is expected to fail soon.

This research project will focus on using recurrent neural networks on the dataset published backblaze to predict failure of hard disk drive. We will use feature selection techniques to identify the attributes from the SMART monitoring system that can increase the accuracy of our prediction.

2. Related Research

HDD failures prediction has been a hot topic in industry and the academia due to its significance in lowering operations cost. Researchers have used regression, decision trees and classification to predict HDD failures.

(Yang et al., 2020b) proposed a Long short-term memory-based model for prediction of disk failure. During training - the disk is classified as failure or normal. Long Short-Term is considered to be improved version of RNN as it has better results with sequential data/ time series data.

(Santos Lima et al., 2017) presented a different approach by estimating remaining useful life. This model can predict failures using long short-term memory for both long term intervals and short-term intervals. They proposed a three-step method: RUL (Remaining Useful Life) binning, LSTM based Model Creation and failure prediction.

(Rincón et al., 2017) investigated multiple machine learning algorithms such as Neural Networks, Decision Trees and Logistic Regression using the backblaze data for training and validation. They focused their study on a heterogeneous disk population. They were able to predict 52% of all disk failures in an heterogenous environment.

(Jiang et al., 2019b) suggested the use of generative adversarial network (GAN) for anomaly detection to predict hard disk failures. They transcribed non-image data (SMART attributes) in 2D images which enabled application of deep learning techniques. Since supervised machine learning methods have good results with balanced datasets, they propose this solution to deal with data imbalance phenomenon as healthy disks are much larger in count than that of failed instances.

(Li et al., 2019) identified LSTM and XGBoost perform way better when compared to support vector machine. Ensemble learning method (stacking) is used to fine tune the results.The output from Long short-term memory model is given as input from the ensemble learning method.They claim accuracy of 78% while predicting failures within 42 days.

3. Aim and Objectives

The aim of this project is to develop a RNN based model to accurately predict hard disk drive failures.

The objectives of this research are based on the aim of this study. They are:

- To implement a RNN based prediction model based on the SMART data to predict HDD failures.
- Optimize the model for accuracy and reduce false positives (Marking good disks as bad)
- To evaluate the accuracy of the RNN based model against existing models that predict HDD failures.

4. Significance of the Study

Recurrent neural networks have seen good amount of success with solving various machine learning problems such as in computer vision, image processing and natural language processing. SMART data provides us with attributes to identify possible disk failures. Identifying possible failures accurately will help to avoid performance degradation/data corruption. Pre-emptive migration of data can reduce risk of data loss. For the datacenters, timely detection will assist in planning the inventory of disks and avoid possible impact to the service. The model needs to reduce false positives since wrong predictions will be additional costs to the datacenter.

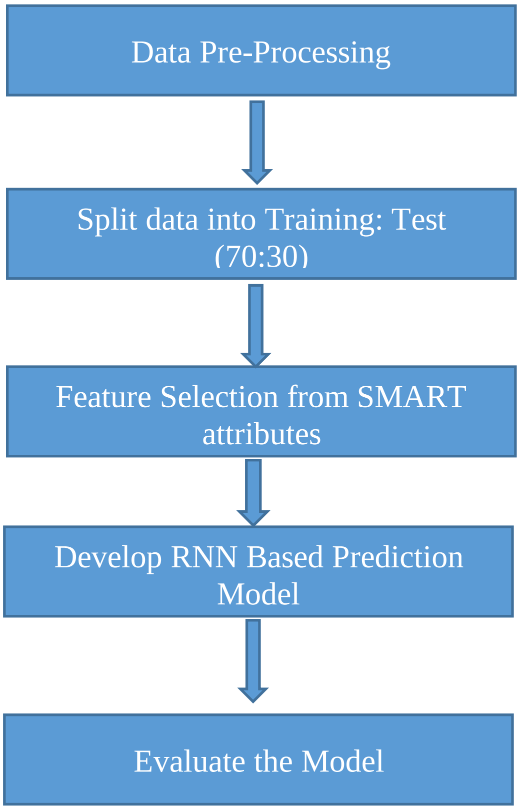
5. Scope of the Study

The scope of this research is limited to:

1. Predictable disk failures
2. SMART data attributes in dataset published by the blackblaze from 2013-21.

6. Research Methodology

The research will apply one of artificial recurrent neural network algorithms to predict failures of HDD. The dataset used is published by backblaze. First, we will perform exploratory data analysis and clean the data. Once the dataset is primed for use, we will use 70% of the dataset to train the model. We'll perform feature selection to identify most impactful attributes from the list of SMART attributes in the dataset. We will use long and short-term prediction results to evaluate the proposed model.



Flow chart – Building the RNN Prediction Model

6.1 Data Selection

SMART data in general is a very sparsely populated dataset. The dataset selected for this research is available publicly (Backblaze, 2022). This dataset contains S.M.A.R.T attributes and values collected from datacenter related to different models of hard drive. SMART attributes have raw values decided by the manufacturer. The maximum value varies from vendor to vendor. It is also possible that same vendor has different maximum values for different models of hard disk drive.

6.2 Data Pre-processing

Since the dataset contains heterogenous mixture of different models from different years, we will have to apply data pre-processing techniques to prime the dataset. We will group the data by hard disk models. To avoid data imbalance, we will only consider hard disk models which meets minimum threshold criteria of failures.

6.3 Model Evaluation

Once the data is primed for use, we will split the data into 70:30 for training and test. Model evaluation will be based on accuracy of detection of failures. We will compare the model with existing LSTM based models as benchmark.

7. Required Resources

The project will be implemented using:

1. Python, as programming language
2. Pandas and NumPy libraries
3. Keras, Neural Network library
4. Google Colaboratory

8. Research Plan

Gantt chart for the proposed plan of Research

The Gantt chart above shows the timeline of the research plan.

8.1 Risks and Contingencies

The risks identified are as follows:

1. Dataset contains about 15GB of data (2013-2021) published by blackblaze. Since the datasets is large, it may act as a bottleneck. If it acts as a blocker, we will train with smaller datasets limited to recent years.

2. Data Imbalance could be a problem as in some years the number of healthy disks vastly outnumber the failed disks. To deal with this problem – we will select hard disks models where certain threshold of failure cases is met.

3. SMART attributes in the datasets varies quarter to quarter. In the recent years, more attributes are included but if we need to use the dataset prior to 2015, we may be limited to 40 SMART attributes.

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APPENDIX II: CODE, DATASET AND GITHUB LINK

DATASET LINK: Backblaze Dataset (Q1, 2021)

CODE LINK:

1_Heterogeneous_LSTM.ipynb
2_Heterogeneous_Bi_LSTM.ipynb
3_homogeneous_LSTM.ipynb
4_homogeneous_Bi_LSTM.ipynb