



# A Comparison Of Parametric Survival Models For Patients With Diabetes Mellitus Retinopathy And Mucormycosis

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**Abstract:** The aim of this study was to compare the effectiveness of parametric models in predicting the factors affecting the retinopathy diagnostic time in Mucormycosis patients. Mucormycosis infection affect noise and then progress to the eye. A parametric survival model of Exponential, Weibull, Log normal and Log logistic were worned to determine effective factors on the time to Retinopathy. The performance of the models was compare with Akaike's Information Criterion (AIC). AIC calculations were performed using R software. Weibull model has minimum AIC values as compared with other parametric models. As a result we concludethat Weibull model is best fit for Patients with Diabetes Mellitus Retinopathy and Mucormycosis [PDMRM].

**Keywords:** Mucormycosis, Diabetic Retinopathy, Parametric models, Akaile information criteria, Diabetes Mellitus Type II, Survival Analysis

## 1. INTRODUCTION

Diabetes mellitus (DM) is a chronic disease. DM occurs either when the pancreas does not produce enough insulin, or when the body cannot efficiently use the insulin [1]. Mucor is a a fungus present everywhere in the soil. Mucormycosis occur in patients low resistance [2]. Survival analysis is a collection of statistical procedures for data analysis for which the outcome variable of interest is time until an event occurs [3]. Types of studies with survival outcomes are clinical trials, observational studies and experiments. Survival analysis is to predict the time-to-an event data. The data describe the time for an event. The event can be death or failure, the data is censored as loss to follow up, withdraw from the study or event not occurred in the study time. Parametric models are occasionally used in the analysis of clinical studies. Parametric models have advantages over Cox's model [4]. Diabetes mellitus is a condition that occurs due to no more use of glucose. The levels of glucose in the blood are controlled by a hormone insulin. One of the disorders of the eye that may occur to the PDMRM [5]. DR is a chronic progressive, potentially sight-threatening disease of the retinal microvasculature. The diabetic patient age is an vital nonmodifiable risk factor and other risk factors like hypertension, hyperlipidemia, microalbuminuria, and anemia. Visual loss in patient with Diabetes Retinopathy can occur intraocular hemorrhages and retinal detachment. Diabetic retinopathy cause eye loss and even blindness to the diabetes patients. Diabetic retinopathy may not have any symptoms, but the disorder which cause blindness besides of cataracts, glaucoma and macular degeneration.

## 2. DATA AND METHODOLOGY

### 2.1 Study area and source of data

Survival analysis includes parametric, non parametric and semiparametric methods. In this study parametric models like Exponential, Weibull, Log-normal, Log-logistic were used for estimation. The data for this study were retrieved from the Harshini Multispecialty Hospital, Madurai, between the time interval of April 2021 and August 2021. The entry point of each patient was different, and the event of interest in this study was status of the operation, is loss of eye by the disease diabetes retinopathy. The diabetes patients were tested for covid 19, and then diagnosed for mucormycosis. The survival time was taken to be censored, amount of underreported data and dropping of missing columns in a total of 169 patients were considered. Survival time was computed by taking the difference between the date on which each sample patient tested positive for the infection of covid 19 and the date of the mucormycosis. The inclusion criteria for each patient were age, gender, rt-pcr test, systematics illness, ct-score, type of mucormycosis, and eyelost status. The flowchart shows the selection of patient in figure 1. The patient with diabetes, result of covid 19 and then selected the status of PDMRM. The patient survival time to predict the diabetes retinopathies were considered to study is shown in the Table 1.

Covariates	Category
Age	Number (28-87)
Gender	Female (59)
	Male (110)
Systematics Illness	Diabetes mellitus (121)
	Hypertension (48)
RT-PCR test	Positive (155)
	Negative (14)
Covid Status	Negative (14)
	Positive (155)
Type of Mucormycosis	Pulmonary - Lung (3)
	Socs – Sinuses (139)
	Serology-based Point-of-care (17)
Eyeloststatus	No (115)
	Yes (54)

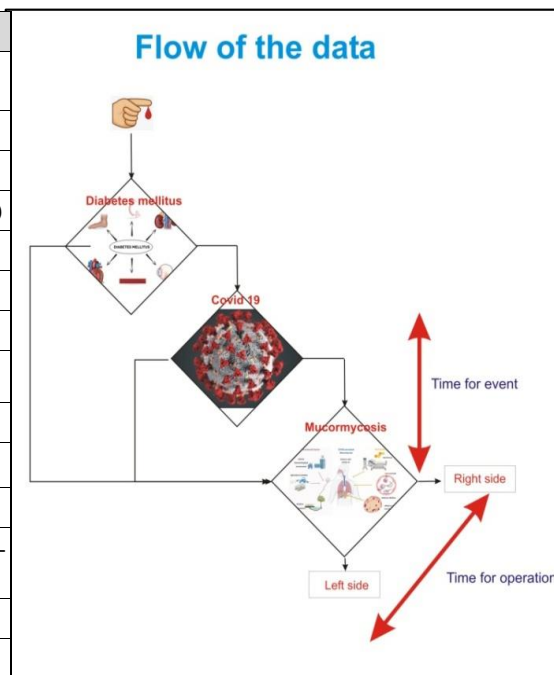


Table 1: Covariates for the study

Figure :1 Flowchart of the selection of patient

## 2.2 MODELS AND ALGORITHMS

### 2.2.1 Methods of Data Analysis

In survival analysis Cox Proportional Hazard mode, Kaplan Meier method and parametric models (Exponential, Weibull, Log-normal, and Log-logistic) were used to estimate. In parametric survival models, survival time follows distribution as Exponential, Weibull, Log-normal, and Log-logistic. The exponential distribution only supports a constant hazard, Weibull, Gompertz, and Gamma distributions support monotonically increasing and decreasing hazards, the Log logistic and Log normal distributions support monotonically decreasing hazards; and the generalized gamma distribution supports monotonically increasing, and monotonically decreasing hazards. This article provides a review of techniques for the analysis of survival data arising from retinopathy health studies [6].

Survival analysis is widely used in biological organism and failure of mechanical systems. It is a branch of statistical analysis that were commonly used in engineering, economics or sociology. The time to event data, such as death, loss, failure of a equipment. The difference of survival analysis is that it deals with censor data. Censoring is a form of missing data, drop out, fail to followup problem which is commonly seen. Survival function measures the probability of event after certain time which defined as

$$S(t) = \Pr(T > t) \dots\dots$$

Where “t” is time and T is a random variable denoting the time of an event.

### 2.2.2 Weibull distribution

The Weibull distribution is also a generalization of the simple exponential distribution, the most widely used parametric survival model [7]. This parameter is called the shape parameter. The Weibull distribution has numerous applications in life expectancy and survival analysis. The way to interpret this parameter is  $p = 1$ . This means that hazard rate is constant and is exactly same as exponential model  $\hat{p} > 1$ : This means that hazard rate increases as time increases  $p < 1$ : This means that hazard rate decreases as time increases. Mean can shown as  $E(T) = \lambda^{-1}\Gamma(1 + 1/p)$  and variance  $Var(T) = \lambda^{-2}[\Gamma(1 + 2/p) - \{\Gamma(1 + 1/p)\}^2]$

### 2.2.3 Exponential distribution

Exponential distribution are often used to model survival times, it is memory less and the hazard function is constant over time[8]. The probability of observing a survival time is exponentially distributed. The exponential distribution has constant hazard  $\lambda(t) = \lambda$ . The survival function is  $S(t) = \exp\{-\lambda t\}$  and the density is  $f(t) = \lambda \exp\{-\lambda t\}$ .

Mean can shown as  $E(T) = 1/\lambda$  and variance  $var(T) = 1/\lambda^2$  Coefficient of variation is 1

### 2.2.4 Log-logistic

The log-logistic distribution is a parametric model with positive random variable for survival analysis [9]. It is used when survival rate increases at starting and decreases thereafter The hazard itself is monotone decreasing from  $\infty$  if  $p < 1$ , monotone decreasing from  $\lambda$  if  $p = 1$ , and similar to the log-normal if  $p > 1$ . The log-logistic distribution has probability density function as

$$f(t) = \frac{\left(\frac{\beta}{\alpha}\right)\left(\frac{t}{\alpha}\right)^{\beta-1}}{\left[1+\left(\frac{t}{\alpha}\right)^\beta\right]^2}, t > 0$$

### 2.2.5 Lognormal distribution

The hazard function of the log-normal distribution increases from 0 to reach a maximum and then decreases monotonically, approaching 0 as  $t \rightarrow \infty$ . It is of interest to study the change points of the failure rate. Log-normal regression is a location-scale model. The log-normal distribution is another commonly used parametric distribution for characterizing the survival time. Lognormal model fits the medical data[10][12].

$LN(\mu, \sigma^2) \sim \exp\{N(\mu, \sigma^2)\}$ ,  $E(T) = e^{\mu + \sigma^2/2}$ ,  $Var(T) = e^{2\mu + \sigma^2}(e^{\sigma^2} - 1)$

### 2.2.6 Akaike information criterion

The Akaike information criterion (AIC) is an estimator of prediction inaccuracy for a given set of data and their quality of statistical models. AIC criterion is used to find best fitted model on clinical data. The AIC is developed by Hirotugu Akaike in 1974 [11]. Goodness of fit for estimating statistical model can done using AIC. The value of AIC is calculated by  $AIC = 2k - 2 \ln(L)$ , where  $k$ =no. of estimated parameter.  $L$  = maximum value of likelihood function. Akaike's information criterion (AIC) measure up to the quality of statistical models.

### 3. Result and Discussion

#### Result

This study has 169 patients observations related to Mucormycosis patient with diabetes retinopathy operation and status of it. Parametric survival models exponential, Weibull, log-normal, and log-logistic distributions were illustrated on this data along with their AIC values[13]. It is found that Weibull distribution is best fitted with low AIC value (1307.668) is shown in Table 2.

**Table 2: Performance of different Parametric Models**

Study Variable	Models	AIC Value
Age + Type of Mucormycosis	Exponential	1692.217
	Weibull	1307.668
	Lognormal	1312.025
	Log-Logistic	1315.496

#### Discussion

In this study, we have evaluated the performance of various parametric models in survival analysis of patient with Mucormycosis. Parametric models provide suitable interpretation based on a particular distribution of time to event. The main objective of this study was to demonstrate the application of parametric models. Keeping this in view, we have applied four widely used parametric models on diabetes retinopathy data. Many research studies have been conducted for diabetes retinopathy[14]. Performance among parametric models with efficient result of AIC. A model with minimum AIC was considered as a best model for mucormycosis patients. AIC values of various parametric models show minimum AIC for Weibull model. In our data of mucormycosis, Weibull model is fitted better than other models[12][15]. It is also cited that eye lost rate in mucormycosis follow-up is more. In our data we calculated for age and type of Mucormycosis. None of other factors were found to be significant effect for the loss of eye in diabetic patients.

### 4. Conclusions and Recommendation

#### Conclusion

The objective of the study was to identify best parametric model to predict diabetes retinopathy for mucormycosis patient who have been under followup at Harshini Hospital. For determining the risk factors for the survival of diabetic patients and modeling the survival time, a total of 169 patients were included in the study out of which 59 were females and 110 were males. Exploring parametric survival models in daily practice of PDMRM research is challenging. This paper provides the application of parametric survival models by R software. It is expected that this Analysis of Diabetes Mellitus Retinopathy for Mucormycosis Patients work can be useful to apply parametric survival models.

#### Recommendations

The result of the study of different factors are identified for the lost of eye for diabetic Retinopathy Patients. Recommendations are made to the government and concerned bodies that they should work on perception about the mucormycosis disease and its risk factors, so that patients should be well informed about the Diabetes retinopathy, early diagnose and to follow up diabetes mellitus status, to minimize the risk of lost of eye[13]. Future studies also need to assess the level of awareness, treatment and control of these factors. The economic and social consequences of diabetes mellitus and other chronic diseases should also receive due attention in future research to the individual and the society at large.

**Reference:**

1. World Health Organization: Global report on diabetes. 2016; 1–88. Available from: [http://apps.who.int/iris/bitstream/handle/10665/204871/9789241565257\\_eng.pdf;jsessionid=DE86065D8957A520439F6D8228C79DA1?sequence=1](http://apps.who.int/iris/bitstream/handle/10665/204871/9789241565257_eng.pdf;jsessionid=DE86065D8957A520439F6D8228C79DA1?sequence=1).
2. Mucormycosis in COVID 19. AIIMS Guidance <https://covid.aiims.edu/mucormycosis-in-covid-19> accessed 26 May 2021
3. David G. Kleinbaum Mitchel Klein, *Survival Analysis: A Self-Learning Text*. USA: Springer Science+Business Media, LLC 1996, 2005, 2012
4. Nardi A, Schemper M. Comparison Cox and parametric models in clinical studies. *Stat Med*. 2003;22(23):3597-3610. [PubMed] [Google Scholar]
5. Srinivasan R. Diabetes mellitus: Can retinopathy be far behind?. *J Curr Res Sci Med* 2018;4:78-80
6. S D Permai and B J Randa, Survival analysis for diabetic retinopathy in diabetic patients using Extended Cox Model, doi:10.1088/1742-6596/1988/1/012113 [http://www.sortie-nd.org/lme/Statistical%20Papers/Burnham\\_and\\_Anderson\\_2004\\_Multimodel\\_Inference.pdf](http://www.sortie-nd.org/lme/Statistical%20Papers/Burnham_and_Anderson_2004_Multimodel_Inference.pdf)
7. W. Weibull, "A Statistical Distribution functions of Wide Applicability", *JApplMech*, Vol,18, Issue.2, pp. 293 – 297, 1951.
8. Jerald f. Lawless, "Statistical Models and Methods for Lifetime Data" Second Edition 2003 by John Wiley & Sons. Inc.
9. Collett, David (2015). *Modelling survival data in medical research* (3rd ed.). Boca Raton: Chapman and Hall / CRC. ISBN 978-1439856789.
10. <https://www.researchgate.net/publication/4791178> The Lognormal Distribution as a Model for Survival Time in Cancer With an Emphasis on Prognostic Factors
11. Burnham, K. P.; Anderson, D. R. (2004), "Multimodel inference: understanding AIC and BIC in Model Selection" ([http://www.sortie-nd.org/lme/Statistical%20Papers/Burnham\\_and\\_Anderson\\_2004\\_Multimodel\\_Inference.pdf](http://www.sortie-nd.org/lme/Statistical%20Papers/Burnham_and_Anderson_2004_Multimodel_Inference.pdf)) (PDF), *Sociological Methods & Research*, 33: 261–304, doi:10.1177/0049124104268644 (<https://doi.org/10.1177%2F0049124104268644>), S2CID 121861644 (<https://api.semanticscholar.org/CorpusID:121861644>).
12. Burnham and Anderson (2003) Model Selection and Multimodel Inference: A Practical Information-Theoretic Approach. Springer Science & Business Media.
13. Dirk F. Moore, *Applied Survival Analysis using R*, Springer International Publishing, May 2016
14. Williams R, Airey M, Baxter H, Forrester J, Kennedy-Martin T, Girach A, *et al*. Epidemiology of diabetic retinopathy and macular oedema: A systematic review. *Eye (Lond)* 2004;18:963-83.
15. Mukesh Kuma, Parametric survival analysis using R: Illustration with lungcancer data, Department of Statistics, M.M.V, BanarasHindu University, Varanasi, India