Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 32 No. 3 (2025)

Application of a Non-Mixture Cure Rate Model for Analyzing Survival of Patients with Brain Cancer

Awaz Shahab Mohamad[1], Prof. Dr. Kurdistan Ibrahim Mawlood[2], Prof. Dr. Nejmaddin Abdulla Sulaiman[3]

[1,2,3] Department of Mathematics, College of Education, Salahaddin University-Erbil, Kurdistan region, Iraq.

Awaz.mohamad@su.edu.krd[1], kurdistan.mawlood@su.edu.krd[2], nejmaddin.sulaiman@su.edu.krd[3]

Article History:

Received: *11-08-2024*

Revised: *01-10-2024*

Accepted: *11-10-2024*

Abstract:

The results of the discovery of very good treatments for all types of cancer in recent years have led to a decrease in mortality. We deal with these observations as cure or immune and models for survival data which involve cure fraction are known as cure rate models or long-term survival models. Methods and Materials, during the past few decades the statistical methods for survival analysis of data have found applications in wide range of fields especially in medical researches, The aim of this research is to study the most factors affecting of brain cancer in Erbil city using Weibull parametric and Logistic-Cox non mixture cure survival models for modelling and identifying the most affecting factors of brain cancer in our data. The data used in this research was obtained from Rzgari Hospital for Cancer in the Kurdistan Region of Iraq – Erbil. The results for our data showed that Extent and Histopathology are the most important factors affecting the brain cancer.

Keywords: Non mixture cure survival models, Weibull parametric model, Survival Analysis, Brain Cancer.

1.INTRODUCTION:-

The time-to-event data illustrates the duration of time from a well-defined time origin to a clearly defined endpoint of interest (event). Despite the fact that time-to-event analysis and time-to-event data are employed more frequently than survival analysis and survival data, the latter term is more precise and comprehensible. Survival analysis is the term used to describe the examination of time-to-event data. The time-to-event data illustrates the duration of time from a well-defined time origin to a clearly defined endpoint of interest (event). Despite the fact that time-to-event analysis and time-to-event data are employed more frequently than survival analysis and survival data, the latter term is more precise and more direct. (Arth, 2012)

The time origin is the diagnosis of a particular form of cancer, and the time endpoint is the death caused by that cancer in the context of cancer research. Alternatively, research may observe participants from the moment of their birth (time of origin) until the onset of a disease (endpoint), this is the method by which time is measured. The data on the time to occurrence is typically collected prospectively over time, typically for a clinical experiment or a future cohort study. Occasionally, information can be acquired retrospectively by consulting medical records or conversing with individuals who have a specific disease (Khawar, 2019). In 2018, the World Health Organization (WHO) reported that cancer is the estimated cause of one in six fatalities. In general, cancer is a disease that results in uncontrolled cell growth, division, and proliferation. Brain cancer is the result of the proliferation of abnormal cells within the brain. Symptoms associated with all types of brain tumors may differ depending on the tumor's size and the segment of the brain that is affected (Nwobl & Ugomma, 2014)

Medical researchers are primarily interested in investigating the impact of multi-explanatory variables on the time to occurrence of a specific event. This event may include mortality, relapse of a specific event, divorce, recurrence of a disease, and so forth. The Cox proportional hazard model is the most frequently employed semi-parametric approach when the primary objective of survival data analysis is to estimate the effect of a covariate.

(Yu, 2008). In general, the event under study will eventually affect all patients if the follow-up period is long enough when using models for survival data. (Cox, 1972). The presence of censored observations is one of the most critical characteristics of survival data. These observations are either lost during the follow-up or are cases that do not experience the event under investigation during the study period. Additionally, there may be instances in which the event of interest is never encountered for certain outcomes (Lambert, 2007). As a result of significant progress made in the treatment of many types of cancers during the last few decades, there have been an increased number of patients who do not experience the event under study (Lambert et al., 2007; Rondeau et al., 2013). The term "cured," "immune," or "non-susceptible" is used to describe cases that do not encounter the event of interest. For instance, researchers may be intrigued by the examination of organ rejection following transplantation. A significant number of cases may never reject transplanted organs; consequently, there is a proportion of the population that has been cured. Cox's proportional hazard model or log-rank test are conventional survival analysis methods that are applicable when the cure fraction is present in the data may not be appropriate because they do not account for the possibility of cure (Arano et al., 2010). In order to address this situation, cure rate models (also referred to as long-term survival models) were created as a distinct form of survival analysis model. The cure fraction may provide more valuable insights into time trends in the survival analysis of cancer patients and may be of significance to patients, clinicians, and policy makers (Andersson et al., 2011). As a result of the substantial advancements in therapies in recent years, there has been a heightened emphasis on the analysis of survival data using these types of models in all disciplines (Corbière and Joly, 2007; Ortega et al., 2014). Additionally, these survival models are referred to as divided population models in the context of economics and other social sciences (Schmidt and Witte, 1989). Cure rate models are pertinent to a variety of cancers, including prostate, breast, melanoma, non-Hodgkin's lymphoma, leukemia, and head and neck cancer, in which a substantial number of cases are immune to the event being studied (Chen et al., 1999; Ortega et al., 2008). Use of cure rate models for survival data analysis is advised when the survival trajectory reaches a stable plateau at the conclusion of the study (Kim et al., 2013). Additionally, the cure rate models will be converted to standard survival analysis models in the absence of a cure fraction (Yu, 2008). Martinez introduced a Bayesian analysis of the four-parameter generalized modified Weibull (GMW) distribution in the presence of cure fraction, censored data, and covariates in 2013. Mixture and non-mixture formulation models are taken into account to account for the proportion of "cured" patients. They contemplated an application to data from patients with gastric adenocarcinoma in order to demonstrate the model's capability to analyze real data. Markov Chain Monte Carlo (MCMC) methods are employed to derive inferences (lawless, 2003)

(Alhasawi, 2015) provided treatment for patients with prostate cancer, investigated the survival analysis to determine and approximate the median duration and survival function of primary and metastatic prostate cancer tumors. The Kaplan-Meier method was employed to evaluate the goodness of fit of the candidate models, and it was found to be an effective factor in the development of prostate cancer. This was determined by the use of residual criteria. The data was subjected to the Accelerated Failure Time (AFT) with four distributions: Exponential AFT, Weibull AFT, Log-Normal AFT, and Log-Logistic AFT. The optimal model for the data was determined to be AFT with Weibull distortions (Sposto, 2002)

(Mawlood, 2019) implemented two advanced statistical methodologies to determine the most influential variables that affect leukemia in Erbil City: logistic regression and Cox regression. The results indicated that the surgery is the most significant factor affecting the survival of leukemia patients in both procedures.

(Mawlood,& Obid, 2019) employed two survival models–the proportional hazard and Accelerated Failure Time Models–to identify the significant factors that influence chest cancer. They discovered that the Cox-PH and AFT models do not identify the same prognostic factors that influence the survival of patients with chest cancer. The objective of this study is Utilizing the Weibull and Logistic-Cox non-mixture cure rate models, to examine the impact of brain cancer patients' clinical, pathological, and biological characteristics on their survival.

2. Materials and Methods:-

The analysis of durations to events, or lifetimes, is the subject of survival analysis. Parametric models are employed to represent the distributions of lifetimes and their correlation with explanatory variables or covariates. These models include the exponential, Weibull, and Log-Normal distributions, as well as the Log-Logistic distribution and associated methods of inference using linear models for log lifetimes. The description and illustration of Accelerated Failure Time (AFT) Models are provided (Lawless, 2003)

The AFT Model is a parametric model that offers a viable alternative to the proportional hazards models that are frequently employed. In contrast to a proportional hazards model, which assumes that the effect of a covariate is to multiply the hazard by a constant, an AFT model assumes that the effect of a covariate is to accelerate or decelerate the life course of a disease by a constant. This is particularly appealing in a technical context where the 'disease' is the outcome of a mechanical process with a well-defined sequence of intermediary phases (Baghestani, & Majd, 2015)

The Logistic-Cox model is a widely used method in the analysis of non-mixture cure survival. It integrates a logistic model for the cure fraction with a Cox proportional hazards model for the uncured individuals. The probability that an individual is "cured" (i.e., does not experience the event of interest during the observation period) is estimated using a logistic regression model. The Cox proportional hazards model is employed to model the survival periods of those who are not cured ((AhmadReza & Moghaddam, 2015)) .

3. Data Collection:

in this research the data consisted of (316) cases obtained from the official database of the Rzgari Hospital for Cancer in the Kurdistan Region of Iraq - Erbil, where these data were collected by patients through direct contact between the specialist doctor and patients. In this study. Data were collected during (4) years. Starting from January 1, 2020 until December 31, 2023 for all brain cancer patients. During the study period (220) patients died and (95) survived under censored, the survival time was measured in months and the data contained (14) variables shown below:

Table (1) variable categorization

Factors	Name	categorization	Frequency	Percent %
Age of Group	**Age of patient at time of diagnosis**	from 15 t022 =1	22	7.0
		from 23 to 30=2	29	9.2
		from 31 to 38=3	57	18.1
		from 39 to 46=4	52	16.5
		from 47 to 54=5	73	23.2
		from 55 to 62=6	44	14.0
		from 63 to 70=7	20	6.3
		from 71 to 78=8	16	5.1
		from 79 to 86=9	2	0.6
Gander	**Gender**	Male =1	188	59.7
		Female =2	127	40.3
Morphology	**Morphology is the study of the type, shape, and structure of brain cancer.**	oligoastrocytoma = 1	10	3.2
		astrocytoma anaplastic=2	8	2.5
		glioblastoma NOS=3	103	32.7
		Hemangioblastoma=4	6	1.9
		Medulloblastoma NOS=5	7	2.2
		Glioma=6	10	3.2
		astrocytoma NOS=7	49	15.6
		Astroblastoma=8	8	2.5
		pleomorphic xanthoastocytoma=9	5	1.6
		Chordoma=10	2	0.6
		Oligoastrocytoma=11	3	1.0
		Neurilemmoma=12	2	0.6
		Anaplastic astrocytoma=13	5	1.6
		Glioblastoma multiforme=14	18	5.7
		medulloblastoma nodular=15	2	0.6
		Meningioma, NOS=16	1	0.3
		Meningioma=17	10	3.2
		Astrocytoma=18	3	1.0
		Gliosarcoma=19	7	2.2

		Diffuse astrocytoma=20	6	1.9
		Transitional meningioma=21	1	0.3
		Ependymoma,NOS=22	6	1.9
		Oligodendroglioma=23	1	0.3
		Glioblastoma=24	3	1.0
		Craniopharyngioma=25	1	0.3
		Neurofbromatosis=26	1	0.3
		Medulloblastoma,NOS=27	7	2.2
		Fibrillary astrocytoma=28	1	0.3
		Oligodendroglioma anaplastic=29	1	0.3
		Gemistocytic astrocytoma=30	1	0.3
		Melanoma,NOS=31	2	0.6
		Oligodendroglioma,NOS=32	11	3.5
		Anaplastic meningioma=33	2	0.6
		Ewing's sarcoma=34	1	0.3
		Meningothelial meningioma=35	3	1.0
		Neoplasm, malignant=36	1	0.3
		Glioma, NOS=37	3	1.0
		Mixed epithelioid and spindle cell=38	3	1.0
		Hemangioendothelioma, NOS=39	1	0.3
Status	**An improvement in the status of patients**	Alive =1	95	30.2
		Dead=2	220	69.8
Grade	**grade describes how normal or abnormal cancer cells look under a microscope**	Grade I=1	21	6.7
		Grade II=2	72	22.9
		Grade III=3	46	14.6
		Grade IV=4	145	46.0
		Unknown=5	31	9.8
Occupation	**Occupation**	Employee	103	32.7
		Businessman	64	20.3
		Housewife	122	38.7
		Retired	21	6.7
		Student	4	1.3
		Unemployed	1	0.3
Subsite	**The location of a nod**	Brain NOS=1	211	67.0
		Parietal lobe=2	25	7.9
		Temporal lobe=3	16	5.1
		Overl lesion of brain=4	16	5.1
		Cerebellum, NOS=5	8	2.5

		Frontal lobe=6	27	8.6
		Rt Frontal lobe=7	1	0.3
		Occipital lobe=8	3	1.0
		Frontal Temporal lobe=9	1	0.3
		Ventricle NOS=10	2	0.6
		Brain, NOS posterior fossa=11	1	0.3
		left Temporal=12	2	0.6
		Rt Frontal lobe=13	1	0.3
		Brain stem=14	1	0.3
Extent	**extent Means tumor extention be yond limits of organ of origin.**	Localized=1	155	49.2
		Regional direct extension=2	13	4.1
		Regional direct extension and lymph nodes=3	2	0.6
		Distant Metastasis=4	1	0.3
		Unknown =5	144	45.7
Behavior	**Behavior of stomach cancer is the ability to grow, invade other areas**	Insitu =1	4	1.3
		Uncertain behavior =2	2	0.6
		Malignant=3	309	98.1
Surgery	**Surgical operations to remove cancerous tumors.**	Yes=1	168	53.3
		No=2	147	46.7
Chemo	**Chemotherapy of patient**	Injected Chemotherapy=1	168	53.3
		Does not inject Chemotherapy =No	147	53.3
T	**The size of the node**	T1=1	13	3.5
		T2=2	13	4.1
		T3=3	4	1.3
		T4=4	10	3.2
		Tx=5	275	0.6
N	**The shape of node**	N0=2	36	11.4
		NX=1	279	88.6
M	**The area occupied by the node**	M0=2	41	13.0
		M1=3	3	1.0
		MX=1	271	86.0

- Table (1) shows the age of diagnosis ranged from 15 to 86 years, most of the patients (23.2%) were at the age group of 47 to 54
- In a total of 315 patients (59.7%) were male and 127 patients (40.3%) were female.
- Of the 315 patients with Brain cancer, (98.1%) have Malignant, (1.3%) patients with Insitu and (0.6%) Uncertain behaviour.

- Only 168 out of 315 patients underwent surgery.
- In addition, our result showed that 211 patients (67%) had brain NOS type ,168 patients are received chemotherapy and most of the patients are housewives with (38.7%).

4. Application of Parametric Survival Models for Real Survival Time

Our data consists of 315 cases brain cancer patients the covariates include (Age, Gender , Weight , grade, Statues, **Occupation**, subsite, extend , **Behavior**, **Surgery**, class age , chemo, T, N, M,). (Stat graphics and Stata) software used to fit Weibull parametric models.

4.1: Distribution Fitting for our Data

The first step is to fit the data to examined distributions for survival time in our data, table (2) shows the output of the goodness of fit to determine

which distribution fits the data best using Kolmogorov-Smirnov statistic and Chi-Square goodness of fit test. The test hypothesis is:

H_0: the data fits the specified distribution

H_1: the data not fits the specified distribution

Table (2) Goodness of Fit test for the Weibull Distribution

Distribution	Kolmogorov- Smirnov	P-value	Chi-Square	P-value
Weibull	0.2587	1.133	49.34	2.344

The second column lists the Kolmogorov-Smirnov test statistic, this statistic is used to help determine how good the fit is, the test assumes that the data fits the specified distribution. The P-values for the Kolmogorov-Smirnov test statistic are given in the third column, the fifth column lists the P-value for the Chi-Square goodness of fit test. A low P-value means that assumption is wrong, and the data does not fit the distribution. A high P-value means that the hypothesis is correct, and the data does fit the distribution. Based on the results, it appears that the Weibull distribution is fit the data well.

Table (3) Analysis of Fitting Weibull Model

Parameter Estimates in Weibull Model							
Parameters	**B**	**Standard Error**	**95% Confidence Limits**		**Chi-Square**	**Df**	**P-value**
			Lower	**Upper**			
Constant	-0.6851	1.8128	-4.2381	2.8679	-0.38		0.705
Age	0.0180	0.0396	-0.0594	0.0965	0.46	1	0.648
Gender	0.2732	0.2045	-0.1275	0.6741	1.34	1	0.181
Weight	0.0031	0.0076	-0.0117	0.0181	0.42	1	0.678
occupation	0.1629	0.0973	-0.0277	0.3536	1.68	1	0.094
Grade	0.0385	0.0786	-0.1156	0.1927	0.49	1	0.624
Morphology	-0.0263	0.0101	-0.0461	-0.0064	2.60	1	0.009
Subsite	0.0193	0.0351	-0.0495	0.0883	0.55	1	0.582
Extent	0.0777	0.0286	0.0215	0.1339	2.71	1	0.007
Behavior	0.3270	0.3343	-0.3282	0.9823	0.98	1	0.328

Surgery	-0.0024	0.4320	-0.8492	0.8444	-0.01	1	0.996
Chemo	-0.1267	0.4348	-0.9789	0.7255	-0.29	1	0.771
Classage	-0.2239	0.3250	-0.8604	0.4131	-0.69	1	0.491
T	0.2155	0.1422	-0.0631	0.4942	1.52	1	0.130
N	0.7228	0.9499	-1.1389	2.5647	0.76	1	0.447
M	0.5139	0.7734	-1.0020	2.0298	0.66	1	0.506
Scale	0.8593	0.0530	0.7745	0.9534			

In the result in table (3) the second column presents the regression coefficient. The sign of the coefficients is an important issue to consider.

- In table above there are two variable (Morphology and Extent) significances and another not significances
- The Morphology variable coefficient is negative (β = -0.0263), which means the risk of the death will decrease for Brain cancer diseases, and Chi-Square test value is equal (2.60) and the **Extent** coefficient is positive (β = 0.0777), so the risk of death which is an increase, the Chi-Square test value is equal to (2.71), P-value is showing the significance of the explanatory variables. The significant values for (Morphology and Extent) variables are (0.009< = 0.05 and 0.007< = 0.05), it means that these treatments are significant.
- For the remained variables such as (Age, Gender, Weight, occupation, Grade, Behavior, Subsite, Surgery Chemo, Class age, T, N, and M) the P-values are non-significant as in the Weibull Model.

The survival function for Weibull model is:

$S\,(t;\,X) = \exp\,(-t^{\alpha}\,[\exp\,(-\,b_0 - b_1x_1 - b_2x_2 \ldots\; - b_p\,x_p)])$

When the Regression Coefficient $\boldsymbol{\beta}$ associated with predictor $\boldsymbol{X}$ is the vector of all the fixed variables and $\boldsymbol{\alpha}$ is the scale parameter.

$S\,(t;\,X) = \exp\,(-t^{0.564}$ [exp (0.6851-0.0180 Age – 0.2732 Gender– 0.0031Weight – 0.1629 Occupation – 0.0385Grade +0.0263 Morphology – 0.0193 Subsite – 0.0777Extent – 0.3270 Behavior + 0.0024 Surgery + 0.1267 Chemo +0.2239Classage – 0.2155T – 0.7228 N – 0.5139 M)]).

- Hence, it can write the Weibull Distribution equation with just significant variables:

$S\,(t;\,X) = \exp\,(-t^{0.564}$ [exp (0.6851+0.0263 Morphology – 0.0777Extent)]).

- **the survival model can be written as:**

$\text{Log}\,T_i = B_0 + B_1X_1 + \cdots + B_PX_P + \varepsilon_i$

We fit the survival model above to the data in brain cancer disease.

$$\text{Log } T_i = 0.6851 - 0.0180\text{ Age} - 0.2732\text{ Gender} - 0.0031\text{Weight} - 0.1629\text{ Occupation} - 0.0385\text{Grade} + 0.0263\text{ Morphology} - 0.0193\text{ Subsite} - 0.0777\text{Extent} - 0.3270\text{ Behavior} + 0.0024\text{ Surgery} + 0.1267\text{ Chemo} + 0.2239\text{Classage} - 0.2155\text{T} - 0.7228\text{ N} - 0.5139\text{ M.}$$

5. Logistic-Cox Model non mixture cure survival model:-

One of a popular method for non-mixture cure survival analysis is the Logistic-Cox model. It combines a Cox proportional hazards model for the uncured persons with a logistic model for the cure fraction. For those who are not cured, the survival times are modeled using a Cox proportional hazards model states an estimation of the treatment effect on survival after the amendment for the other descriptive variables. The model-building process takes place in fifteen treatments (AGE , Gander ,Weight, occupation, Grade , Histopathology , Extent , Behavior , Subsite , Surgery, Chemo, Class age , T , N ,and M)

Table (4) Case Processing Summary

Case Processing Summary		N	Percent
Cases available in analysis	Event[a]	220	69.8%
	Censored	95	30.2%
	Total	315	100.0%

Table (4) shows the case processing summary determines whether the event occurred for a specific case or not, the number of cases available in the event analysis is 315 cases, the analysis shows that there are 220 deaths, 69.8% are event data and 95 cases, 30.2%, is the number of patients who are still alive under observation.

Omnibus tests are a type of statistical test for all variables, sometimes called the chi-square test. It is a statistical test carried out on a general hypothesis that tends to find general significance between the variance of parameters. The hypothesis is

H_0 : The model includes explanatory variables.

H_1 : The model not includes explanatory variables.

Table (5) Omnibus Tests of Model Coefficients

-2Log Likelihood	Overall (score)			Change From Previous Step			Change From Previous Block		
	Chi-square	df	Sig.	Chi-square	df	Sig.	Chi-square	df	Sig.
1991.035	213.898	120	.000	77.423	120	.999	77.423	120	.999

Table (5) shows that the value of chi-square = 213.898 at the degree of freedom of 120 and the P-Value 0.000, which means that the statistical model is statistically significant, which indicates that the variables in the model are importance and effect. Thus, we accept the null hypothesis, which states that the explanatory variables are included in the statistical model.

Table (6) Variables in the Equation for Logistic-Cox non mixture cure model

Variable	B	SE	Wald	df	Sig.	Exp(B)	95% Confidence Limits	
							Lower	Upper
gander	-.199	.171	1.360	1	.244	.819	.5858	1.1454
Weight	-.003	.007	.242	1	.623	.997	.9840	1.1454
grade	-.047	.068	.467	1	.494	954	.8348	1.0911
classage	.061	.041	2.236	1	.135	1.063	.9811	1.1518
occupation	-.116	.083	1.961	1	.161	.890	.7566	1.0475
morphology	.023	.009	6.420	1	.011	1.023	1.0051	1.0407
subsite	.002	.030	.003	1	.954	1.002	.9439	1.0631
extent	-.058	.025	5.387	1	.020	.944	.8992	.9910
behavior	-.378	.273	1.907	1	.167	.686	.4010	1.1716
Surgery	-.224	.370	.365	1	.546	.800	.3869	1.6523
Chemo	.328	.376	.760	1	.383	1.388	.6645	2.8971
T	-.159	.114	1.938	1	.164	.853	.6819	1.0670
N	-.638	.772	.683	1	.409	.528	.1163	2.3989
M	-.530	.640	.687	1	.407	.588	.1677	2.0629

Table (6) model fitting and parameter estimation of Logistic-Cox non mixture cure model, if the sign of the coefficients is positive sign means that the hazard (risk or death) is higher, but if the sign is negative it means that hazard is lower.

To understand the effects of each patient, Exp (B) is the expected change in the hazard for a minimum risk.

❖ The value of Exp (B) for surgery gives the meaning of the brain cancer hazard for all patients that made a surgery are 0.800 months.

❖ Extent is one of the effected factor to the risk or death in Brain cancer diseases decease by Exp(-.199) = 0.944 which is increase in the risk of the death for patient with (male or female), the P-value is equal to 0.020 it means that there is a greater risk of death in Brain cancer in both type.

❖ morphology is one of the effected factor to the risk in Brian cancer diseases decease by Exp(0.023) = 1.023 which is decrease in the risk of the death for patient. The significant value is 0. 011<= 0.05 so there is significant effect on Brain cancer.

Here we can see that the (chemotherapy and immune system) are not significant but for patients with chemotherapy and immune system are at higher risk than the other factors.

As shows in the table above column (Wald) test for significant of coefficients, morphology is one of the significant factor in our study because has a greater value in Wald test column is (6.420) with significant value is (0.01 <=0.05). And the results showed that there are significant differences for Extend.

In case, x is the vector of the entire fixed covariates (surgery, radiology, chemo, hormone, sex and immune) and β is the vector of the regression coefficient leading to the fixed covariates.

$$h_i(t) = h_0(t) * \exp(B'x)$$

$$h_i(t) = h_0(t) * \exp(0.01morphology - 0.058\ Extent)$$

6. Comparing Models:-

There are several way to compare survival functions between two or among models, in this study two measures; Akaike's information criterion and Bayesian information criterion are used for Comparing, the Weibull AFT model with Logistic-Cox non mixture cure model and as follows::-

Table (7) comparing models with AIC and BIC

Models	N.of parameters	Log- Likelihood	AIC	BIC
Logistic-Cox	2	-1029.4222	2062.844	2070.35
Weibull FIC	2	-431.0778	870.1552	885.1659

Practically the objective of table (7), determines which of the two models is more suitable in our data (Logistic-Cox model or Weibull AFT Model).

Comparing models with the Akaike's information criterion and Bayesian information criterion is made by calculating each measure for both models.

The model with the lowest AIC and BIC are considered the best model, in our results shows that the Weibull AFT is the best model because AIC=870.1552 and BIC=885.1659 are have lowest values comparing with AIC and BIC in Logistic-Cox model. In order to detect the significant factors on cancer disease after getting these results we find that (morphology, extent) are the most significant factors in Weibull AFT model after comparing the value of significant with the P-value.

Conclusion

1- The distribution of the data was Weibull distribution by testing the data in the easyfit 3.0 program, and the Weibull AFT model fits better and describes the data best.
2- The Logistic-Cox model may be used for many applications because of the relationship between the risks of an event over time.
3- Depending on both used models (Weibull and Logistic-Cox models) the results of this study indicated that the two factors that effected on the brain cancer are (morphology, extent).
4- As a result of parameter estimation by Parameter Estimates in Weibull Model and Logistic-Cox model we found there are to variables effect of death in brain cancer .
5- Comparing the Logistic-Cox model with the AFT model based on the AIC and BIC it is concluded that (Weibull AFT model) is the most suitable model for our data set that was used in this study.

Reference

[1] AhmadReza, B., & Moghaddam, S. S. (2015). Application of a Non-Mixture Cure Rate Model for Analyzing. Asian Pac J Cancer Prev,, 16 , 7359-7363.

[2] Alhasawi, E. (2015). *Survival Analysis Approaches for Prostate Cancer.* Sudbury, Ontario, Canada Laurentian Universite.

[3] Arth, A. (2012). The relationship between the parameterizations of the Weibull model and the Cox hazards model by using application and simulation. *kerbala university*(2), 10.

[4] Abu Bakar MR, Salah KA, Ibrahim NA, et al (2008). Cure fraction, modelling and estimating in a population-based
[5] cancer survival analysis. Malaysian J Mathematical Sciences, 2, 113-34.
[6] Achcar JA, Coelho-Barros EA, Mazucheli J (2012). Cure fraction models using mixture and non-mixture models. Tatra Mountains Mathematical Publications, 51, 1-9.
[7] Akhlaghi AA, Najafi I, Mahmoodi M, et al (2013). Survival analysis of iranian patients undergoing continuous ambulatory peritoneal dialysis using cure model. J Research in Health Sci, 13, 32-
[8] Baghestani, A. R., Moghaddam, S. S., & Majd, H. A. (2015). Survival Analysis of Patients with Breast Cancer using Weibull Parametric Model. *Asian Pacific Journal of Cancer Prevention, 16*, 8567-8571.
[9] Cleves, M. (2010). An Introduction to Survival Analysis Using Stata. Texas: A Stata Press Publication.
[10] Cox, D. (1972). Regression models and life tables (with discussion, journal of the royal statistical society, series b, 34, 187-220.
[11] Ibrahim, J. (2001). Bayesian Survival Analysis, New York: Springer Science Business Media, LLC.
[12] Kirkwood, J. & Strawderman, M. & Ernstoff, M. Interferon alfa-2b adjuvant therapy of high-risk resected cutaneous melanoma: theeastern cooperative oncology group trial est 1684. J Clin Oncol 1996; 14: 7–17.
[13] Lawless, J. (2003). Statistical Models and Methods for Lifetime Data (2nd ed.). Canada: A JOH N WILE Y & SONS, INC.
[14] Lambert, P. &Thompson J. & Weston,C. (2007). Estimating and modeling the cure fraction in population-based cancer survival analysis. Biostatistics, 8, 576-94.
[15] Lambert PC (2007). Modeling of the cure fraction in survival studies. Stata Journal, 7, 351.
[16] Martinez, E.Z., Achcar, J.A., Jácome, A.A. and Santos, J.S.,(2013) Mixture and non-mixture cure fraction models based on the generalized modified Weibull distribution with an application to gastric cancer data. Computer methods and programs in biomedicine, 112(3), pp.343-355.
[17] Mawlood, K. I., & Abdullah, C. S. (2024). Survival analysis of Brain Cancer in Erbil. *union of Arab statisticians*, 1-17.
[18] Mawlood, K. I. (2019). Using Logistic Regression and Cox Regression Models to Studying the Most Prognostic Factors for Leukemia patients. Qalaai Zanist Scientific Journal, 4(2), pp. 705-724.
[19] Nwobl, F. N., & Ugomma, C. A. (2014). A Comparison of Methods for the Estimation of Weibull Distribution Parameters. *Metodološki zvezki*, 65-78.
[20] Moore, D. (2016). Applied Survival Analysis Using R. Piscataway, NJ, © Springer International Publishing Switzerland.
[21] Ortega EM, Barriga GD, Hashimoto EM, et al (2014). A new class of survival regression models with cure fraction. J Data Science, 12, 107-36.
[22] Rondeau, V. & Schaffner, E. & Corbière, F. (2013). Cure frailty models for survival data: Application to recurrences for breast cancer and to hospital readmissions for colorectal cancer. Statistical Methods in Medical Research, 22, 243-60.
[23] Sadjadi, A. & Nouraie, M.& Mohagheghi, A. (2005). Cancer occurrence in Iran in 2002, an international perspective. Asian Pac J Cancer Prev, 6, 359
[24] Schmidt, P. & witte, A. (1989). Predicting criminal recidivism using ‘split population survival time models, Econometrics 40, pp. 59-14
[25] Sposto R (2002). Cure model analysis in cancer: an application to data from the Children's Cancer Group. Statistics in Medicine, 21, 293-312.
[26] Yu X, De Angelis R, Andersson TM, et al (2013). Estimating the proportion cured of cancer: some practical advice for users. Cancer Epidemiol, 37, 836-42